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INFLUENCE OF THROUGHPUT RATE AND INPUT COMPOSITION ON SENSOR-BASED SORTING EFFICIENCY

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ABSTRACT

According to the Directive (EU) 2018/851 of the European Union, higher recycling rates for municipal waste will have to be met in the near future. Beside improvements to the collection systems, the efficiency of mechanical processing and sorting will have to be increased to reach the EU´s targets. Sensor-based sorting (SBS) plants constitute an integral part of today's sorting processes. Two main factors determine the sorting performance: throughput rate and input composition. To improve recycling efficiencies, especially SBS machines need to be optimized. Three evaluation criteria are used to describe the performance of these processes: recovery (content of input material – both eject and reject material discharged into the product fraction) or product quantity (amount of product generated via sorting within a specific interval – calculated by multiplying throughput rate and yield), yield (amount of eject material discharged into the product fraction), and product purity. For this study, 160 sorting experiments each with 1,000 red and white low-density polyethylene (LDPE) chips were conducted to investigate the effects of throughput rate and input composition on sorting processes. This simplified approach reduced the influence of other factors on the sorting performance, giving precise information on the effect of throughput rate and input composition. The testing results can enter process optimization. With increasing throughput rates, product quantity rises following a saturation graph (despite exponential decrease in recovery). In the experiments a higher throughput rate also resulted in an exponential decrease of the yield while a change to the input composition had no such effect. The third evaluation criteria, product purity, decreases linearly with increasing occupation density. The slope of this function depends on the input composition.

1. INTRODUCTION

16.3 million tons (170 kg/capita) of plastic packaging waste (PPW) are produced in the European Union (EU) per year, out of which as little as 42 wt% were recycled in 2016 according to Eurostat, 2019. E. g. by 2025, the EU also aims to increase the rate for preparing for re-use and the recycling of municipal waste to 55 wt% (The European Parliament and of the Council of the European Union, 2018).

PPW-recycling requires separation into individual plastic types (International Organization for Standardization, 2008). Plastics are usually separated using sensor-based sorting (SBS) (Gundupalli et al., 2017; Jansen et al., 2012). Spectral imaging techniques including NIR (near-infrared, 750-1100 nm (Workman and Springsteen, 1998), VIS (visual image spectroscopy, 380-750 nm (Workman and Springsteen, 1998) and HSI (hyperspectral imaging) are most commonly applied though laser-induced-breakdown-spectroscopy and X-ray-sorting are available as well (Table 1).

SBS techniques have been utilised by various industries during the last years. Additionally, research results were published in many papers. SBS is mostly applied in recycling (Gundupalli et al., 2017; Mesina et al., 2007; Rahman et al., 2014), mining (Knapp et al., 2014; Lessard et al., 2014; Dalm et al., 2014) and food (Alaya et al., 2019; Cubero et al., 2011; Tu et al., 2007) processing plants. Sound information on the sorting performance of such technologies is limited, however.

One key parameter found fluctuating in industrial SBS plants is their throughput rate adversely affecting their sorting efficiency (Feil et al., 2019). The throughput rate, in tons per hour, is related to the occupation density (the relative size of the detection zone in an SBS unit that is covered with particles), in %. With respect to SBS, the occupation

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TABLE 1: Sorting techniques applicable to different types of waste (mod. Gundupalli et al., 2017).

	Eddy current	LIBS	X-ray sort	Optical sort	Spectral sort
Non-ferrous metal	✓	✓	✓	✓	✓
Plastic		✓	✓		✓
Paper				✓	
Glass				✓	✓
Wood		✓	✓		

density is a better indicator of capacity than the throughput rate. The reason is that an SBS unit operates differently from other processing technology. Objects must here be presented separately to a sensor enabling a particle-specific sorting decision (eject or reject) by the computing technology. The spatial separation of objects is therefore of utmost importance. Their mass, high or low, in comparison to other particles in the material stream, is irrelevant. The performance of an SBS unit is accordingly related to the space particles occupy in the detection zone and only indirectly correlated with the throughput rate. This paper therefore applies, the occupation density rather than the throughput rate as a reference parameter to describe the capacity of an SBS machine. For industrial applications, conversion into throughput rates considering material-specific grammages is otherwise required.

Fluctuations of the occupation density mostly result from batch processes integrated into an SBS plant, e.g. opening packages or bales. A second key parameter found fluctuating in SBS plants is input composition, because of the delivery of input material from different (urban/rural) regions.

Variations in occupation density and input composition, as well as other factors like surface moisture and roughness (Küppers et al., 2019b), and mechanical stress (Küppers et al., 2019a) can affect the purity and recovery of products in two ways:

- Errors in detection, recognition and classification of particles (sensor and algorithm);
- Errors in mechanical discharge (conveyor belt, chute, pressurized air nozzle bar).

On the one hand, a high occupation density, or throughput rate, may impact the recovery and purity of the output as overlapping particles impede the analysis of the underlying material. Restrictions and a significantly reduced belt speed on standard sorting machines are required especially for sorting light and flat materials, such as films, because of their low weight and high surface coverage (Beel, 2017). On the other hand, high throughput rates are desirable to produce large amounts of products in a short time to be economically sound. No systematic study on the effects of occupation density on SBS of plastics has been conducted yet, however.

The two main factors affecting SBS efficiency, i.e. input composition and occupation density, were addressed in systematic testing series. Data hereby obtained provides insight for better understanding of the efficiency of SBS processes.

2. MATERIAL AND METHODS

2.1 Materials

1,000 rectangular LDPE chips (white and red) were used as input material, each featuring an investigated visible surface area of approx. 18.3 cm², a width of 30 mm, an average length of 61 mm and a thickness of 3 mm (Figure 1).

The grammage of these chips amounts to 0.27 g/cm² and the average particle weight is 4.9 g. In the conducted experiments, white particles were regarded as 'eject' and supposed to be discharged via air shocks while red particles were considered as 'reject' and not supposed to be discharged.

2.2 Equipment

An experimental SBS setup, engineered by Binder+Co AG, was utilized to conduct a total of 160 sorting experiments. As shown in Figure 2, this testing setup consisted of a chute sorter, of a work width and length of 500 mm and 455 mm, respectively, and an upstream vibrating conveyor to feed the sample material. The resolution of the colour sensor is to 0.523 mm x 0.473 mm/px. The valve resolution is 6.25 mm.

Once on the chute, the bulk material was detected using the built in VIS sensor and then classified by means of colour, intensity and brightness. If classified eject material, the respective object was discharged via the compressed air nozzle bar. Any detected object > 35 mm, e.g. multiple particles overlapping, was digitally divided into several objects and then classified individually to be rejected or ejected.

2.3 Preliminary Tests

Preliminary detection tests were carried out to evaluate the content of falsely classified pixels of reject (red) and eject (white) particles. A series of five trial runs was

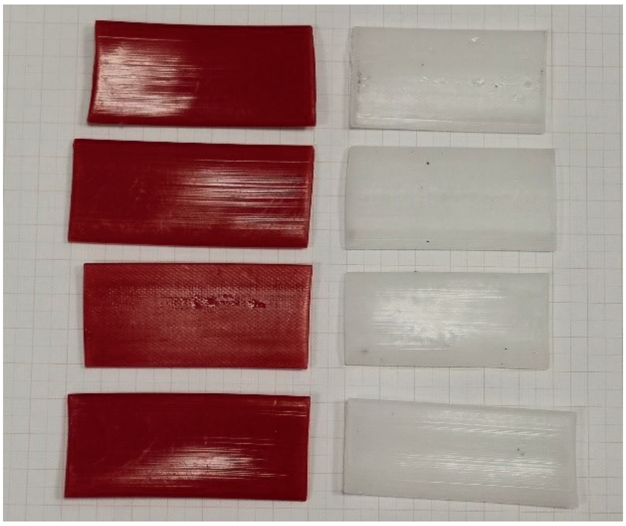

FIGURE 1: Testing material for sorting experiments - red (reject, left) and white (eject, right) LDPE chips.

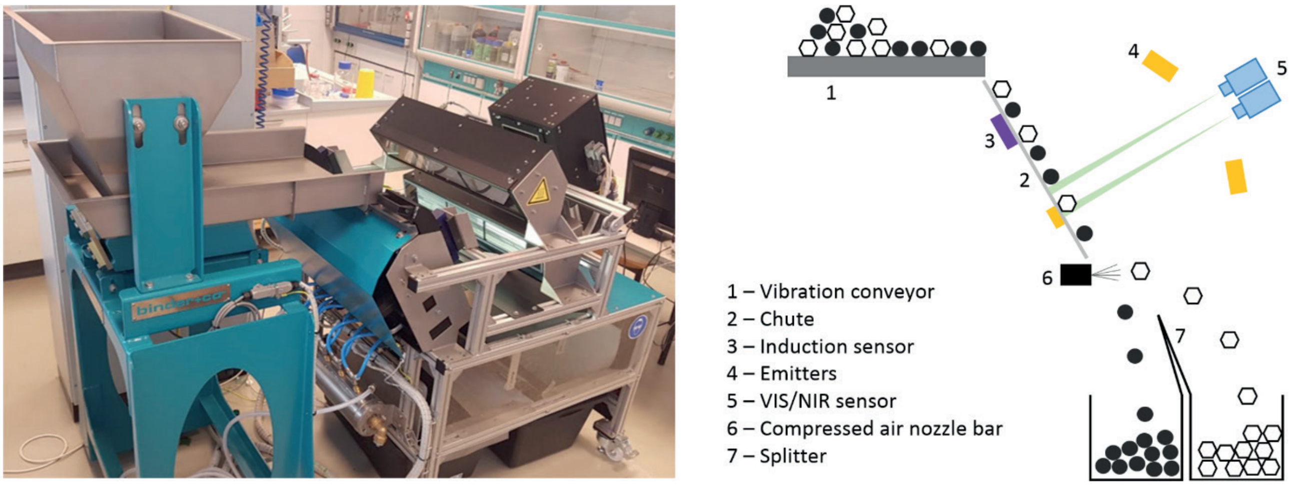

FIGURE 2: Setup for SBS sorting experiments.

conducted featuring 1,000 particles for each particle type (eject/reject). Each time, the content of correctly and incorrectly classified pixels was recorded.

Additionally preliminary ejection tests were carried out to determine the average amount of incorrect discharges based on variable sliding speeds, sideways movement, erratic bouncing, etc. on the chute. For this purpose, in five runs each including 1,000 particles supposed to be discharged, were fed to the sorting machine and overlapping of particles was avoided by feeding the particles one by one to the vibration conveyor, ensuring 100% particle separation. As a result of this approach, the occupation density remained below 2.8% for all preliminary ejection tests. This enabled assessing the effect of purely mechanically-based sorting errors. The results of the preliminary tests were evaluated by counting the number of falsely rejected and correctly ejected particles.

2.4 Main Experiments

To study the effects of input composition on sorting efficiency, eight samples of different composition were created (Table 2), each containing a total of 1,000 chips.

On average, this resulted in 5,500,000 detected object pixels per test run, with a standard deviation of about 200,000 pixels, provided that no particles overlapped. The standard deviation σ was calculated using the following equation, where x is the sample mean, $\bar{x}$ is the arithmetic mean and n is the sample size.

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})}{(n-1)}} \quad (1)$$

TABLE 2: Generated samples and their composition.

Sample number	Sample name	Red particles	White particles
1	(95/5)	950	50
2	(90/10)	900	100
3	(85/15)	850	150
4	(80/20)	800	200
5	(70/30)	700	300
6	(60/40)	600	400
7	(50/50)	500	500
8	(20/80)	200	800

Each of the eight samples was sorted 20 times at varying throughput rates. For each experiment, the respective sample mixture of 1,000 particles was placed on the vibration conveyor and fed to the sorting machine by starting the vibration conveyor after adjusting its potentiometer to the intended testing period. After each experiment the number of ejected and rejected particles (red and white) was determined by manual sorting.

Each experiment required a steady feed, since fluctuations of the throughput rate would have resulted in shifting occupation densities, compromising analysis of the results. The testing period of each experiment could therefore deviate slightly from the intended value. The testing periods of the 20 experiments were as evenly distributed as possible for each input composition, ranging from 1.0 s to 70.6 s. Table 3 shows the relationship of testing period, occupation density and throughput rate per metre of working width.

The occupation density is defined as the ratio of detected object area and available space on the detection area for the testing period. Available space is calculated using the following equation with A=available area, υ=sliding speed of particles at the point of detection (1321 mm/s), t=testing period (cf. Table 3) and w=working width (500 mm).

$$A = \upsilon * t * w \ [m^2] \quad (2)$$

After each experiment the particles were thoroughly mixed to generate a uniform blend of all 1,000 particles designed as input material for the next experiment.

2.5 Evaluation of Results

The results were analysed based on three evaluation criteria attained at the respective throughput rate of each trial:

- Recovery (directly related to product quantity);
- Yield;
- Purity.

TABLE 3: Overview of testing period, occupation density and throughput rates.

Test duration [s]	Occupation density [%]	Throughput rate [t/(h*m)]
1	278.6	35.02
2	139.3	17.51
3	92.9	11.67
4	69.6	8.75
5	55.7	7.00
6	46.4	5.84
7	39.8	5.00
8	34.8	4.38
9	31.0	3.89
10	27.9	3.50
20	13.9	1.75
30	9.3	1.17
40	7.0	0.88
50	5.6	0.70
60	4.6	0.58
70	4.0	0.50
80	3.5	0.44
90	3.1	0.39
100	2.8	0.35

Recovery (R) is defined as the ratio of complete product mass (m_{eject}) and total input mass (m_{input}) per time unit, providing information on the product quantity generated at a respective throughput rate:

$$R = \frac{m_{eject}[\frac{t}{h}]}{m_{input}[\frac{t}{h}]} * 100\ \% \tag{3}$$

Product quantity is directly related to recovery, expressed by the mathematical product of throughput rate (Table 3) and recovery (Figure 3) for a given occupation density:

$$P = m_{input}[\frac{t}{h}] * R \tag{4}$$

The yield (R_w) is based on the amount of the desired component (eject) in the feed material and calculated from the ratio of the mathematical product of determined mass flow (m_{output}) and substance concentration (c_{output}) of the respective sorting product (output) to the respective product of mass (m_{input}) and substance concentration (c_{input}, defined as the content of eject material in the input material) of the feed material (input). It is calculated as follows (Feil et al., 2016):

$$R_w = \frac{m_{output}[\frac{t}{h}] * c_{output}[\%]}{m_{input}[\frac{t}{h}] * c_{input}[\%]} * 100\ \% \tag{5}$$

According to Feil et al. (2016), the purity (P_m) of a material is defined as the content of correctly ejected material in the sorting product. It is calculated as follows:

$$P_m = \frac{m_{recyclable\ material}[\frac{t}{h}]}{m_{impurity}[\frac{t}{h}] + m_{recyclable\ material}[\frac{t}{h}]} * 100\ \% \tag{6}$$

All three performance indicators are usually mass-specific [w%]. When evaluating SBS sorting experiments, however, particle-related [p%] information is more useful, meaning that a sorting stage is evaluated based on the number of particles contained in each output fraction (reject and eject) and not on the mass of the respective fraction. Conclusions on mass-specific evaluation criteria can be obtained by providing the average particle-specific mass. Particle-related evaluation criteria are displayed accordingly in this paper.

3. RESULTS AND DISCUSSION

3.1 Preliminary Tests

During the preliminary detection tests, an average of 0.87% of the pixels of white objects and 0.65% of the pixels of red objects were falsely classified, the edges of objects being most commonly affected. Since all objects containing > 50% pixels of the eject material are discharged and misclassification is evenly distributed among all particles, the misclassification rate is not significant for the discharge of objects.

Although misclassification did not result in a rejection of particles, 0.28% to 0.44% of all eject particles were rejected in the preliminary ejection test. These amounts of falsely rejected particles were only the result of mechanical errors, because quite low throughput rates had been chosen, overlapping cannot be a reason for rejection. The contents of incorrectly detected and incorrectly rejected particles were therefore insignificant for the used experimental setup. The subsequently conducted main experiments thus allow statements to be made about the best operation conditions of sorting stages in treatment plants applying SBS machinery that are based on input composition and occupation density of a sorting stage only.

3.2 Recovery and Product Quantity

The effects of occupation density on the recovery for different input compositions are displayed in Figure 3. Evidently the recovery decreases with increasing occupation density. For rising eject shares of input, maximum recovery increases (usually at the lowest occupation density).

Since industrial applications most often run at quite low occupation densities the graphs for recovery and product quantity in Figure 4 are displayed for occupation densities < 100%. Despite decreasing recovery, product quantity evidently rises with increasing occupation density following a saturation graph.

The slope of shown saturation graphs most often approaches zero when occupation densities reach 40% to 60%. The higher the content of reject particles in the input, the earlier saturation is reached. The slopes of well-balanced inputs (50/50 and 60/40) drop for higher occupation densities. When considering the option of increasing throughput, the result indicates that sorting at high throughput rates may only be reasonable for input material of a balanced composition with regard to product quantity. For other input compositions, high occupation densities show less benefit in this regard.

In general, there are direct correlations observed between recovery and both occupation density and input

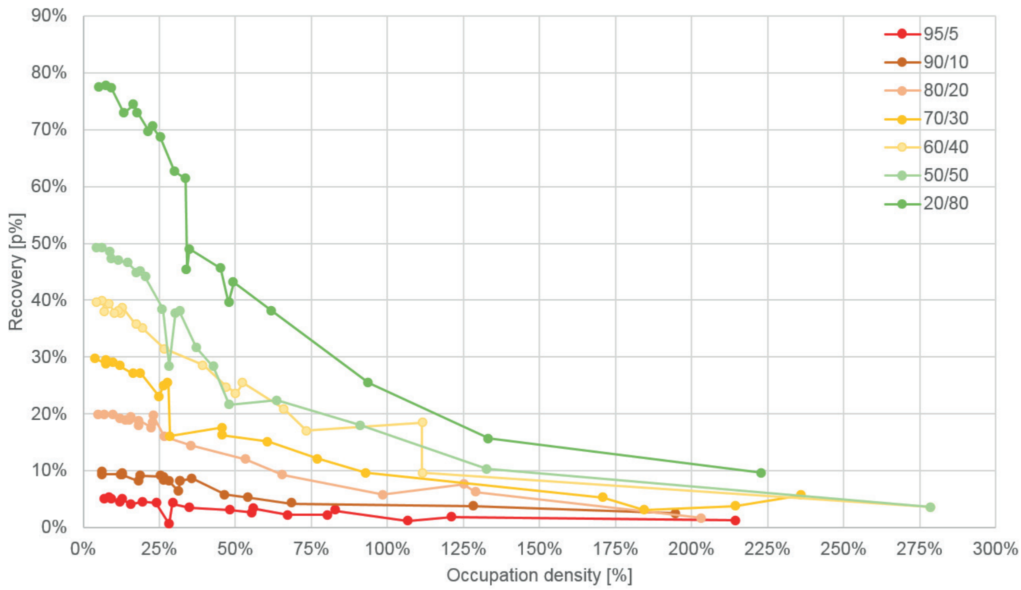

FIGURE 3: Effects of occupation density on recovery for different input compositions – occupation density < 300%.

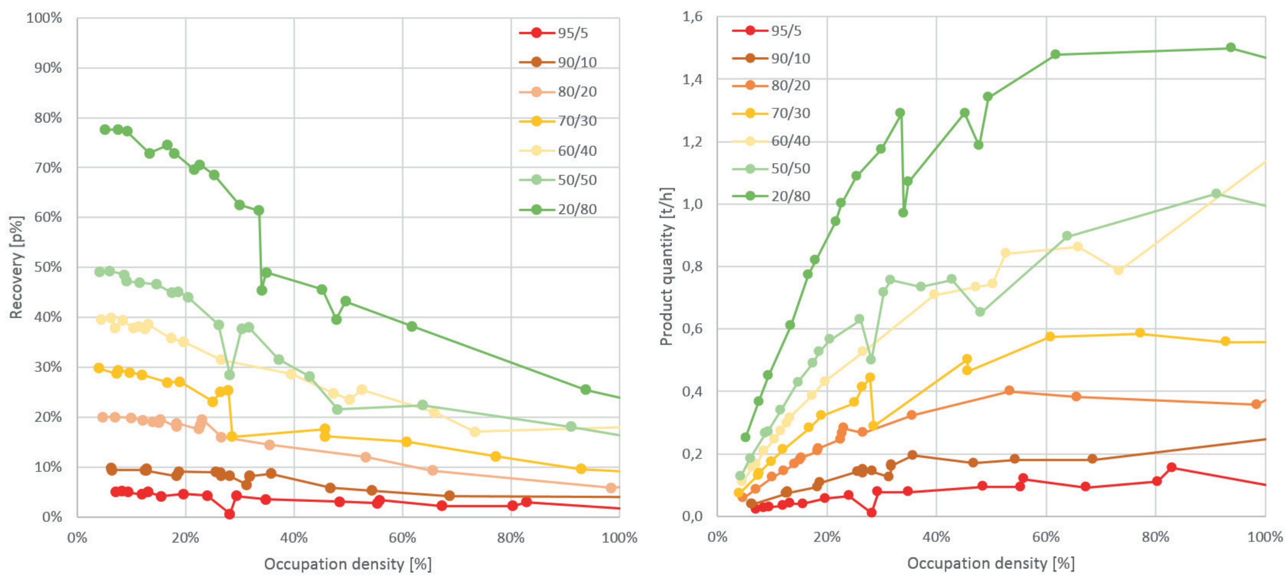

FIGURE 4: Effects of occupation density on recovery (left) and product quantity (right) for different input composition – occupation density <100%.

composition (the content of particle-related eject in input) which may permit forecasting the product quantity as a function of influencing factors. Use Figure 4 to determine the occupation density that is most suitable for a reasonable product quantity, depending on the respective input composition. Note that reject quantity increases with eject quantity.

3.3 Yield

The effect of occupation density on yield for different input compositions is given in Figure 5. With rising occupation density, the yield decreases exponentially from approx. 98 p% to approx. 10 p% for all input compositions identically.

Since industrial applications most often run at occupation densities <<100%, only the selected area shown in Figure 5 (blue frame), was taken into account for further analysis. Figure 5, therefore, gives the graph of the yield for all experiments at an occupation density <100%.

Additionally, the average yield is shown (red) as a polynomial function of the fourth degree with a coefficient of determination of $R^2=0.9417$:

$$y = -5.0564x^4 + 10.321x^3 - 6.2344x^2 + 0.2105x + 0.9784 \quad (7)$$

The inflection points of this approximation function are located at occupation densities of 27.6% and 74.5%. The first inflection point is reached at an occupation density of about 30% where its rising value impairs the yield very much. The second inflection point is reached at an occupation density of 75% when changes to its value have a much smaller impact on the yield. This is consistent with a range of occupation densities chosen for calculating the average yield. Up to an occupation density of 100%, the yield decreases constantly. Beyond, the decrease subsides. If values >100% were included for the occupation density when calculating the approximation function, there was no drop of the polynomial function at an occupation density of 100%.

Figure 6 shows that the occupation density effects the separation of eject particles while the input composition has no effect on the yield. This information helps to determine the highest occupation density while still achieving acceptable eject losses that may be controlled by, e.g., a quota, independent of the input composition.

Note that fluctuations of the yield increase significantly at occupation densities > 27%. This can be traced back to the elevated potential for overlapping as occupation densities increase since overlapping can either lead to eject losses (reject particles covering eject particles leading to reduced yield by rejection of both particles) or to a discharge of reject particles (eject particles covering reject particles leading to increased yield by ejection of both particles).

3.4 Effects on the Sorting of Rejects - Purity

The effects of changes to the input composition and occupation density on the absolute number of reject particles wrongly sorted into the eject fraction are displayed in Figure 7. Up to 35 red particles were sorted incorrectly. For clarity purposes, only trend lines (concave growth curves) are shown alongside the raw data in Figure 7.

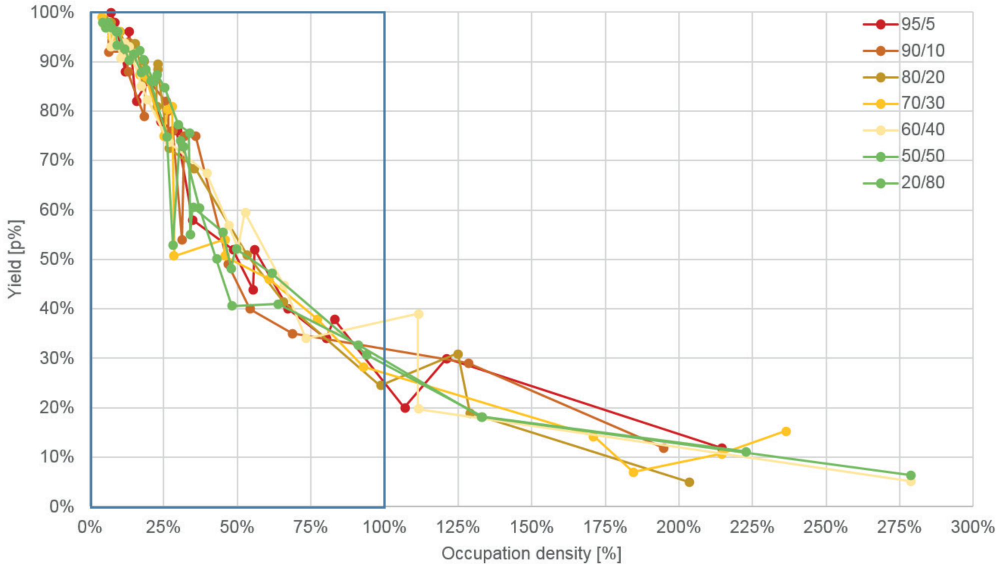

FIGURE 5: Composition-related effects of occupation density on yield - occupation density < 300%.

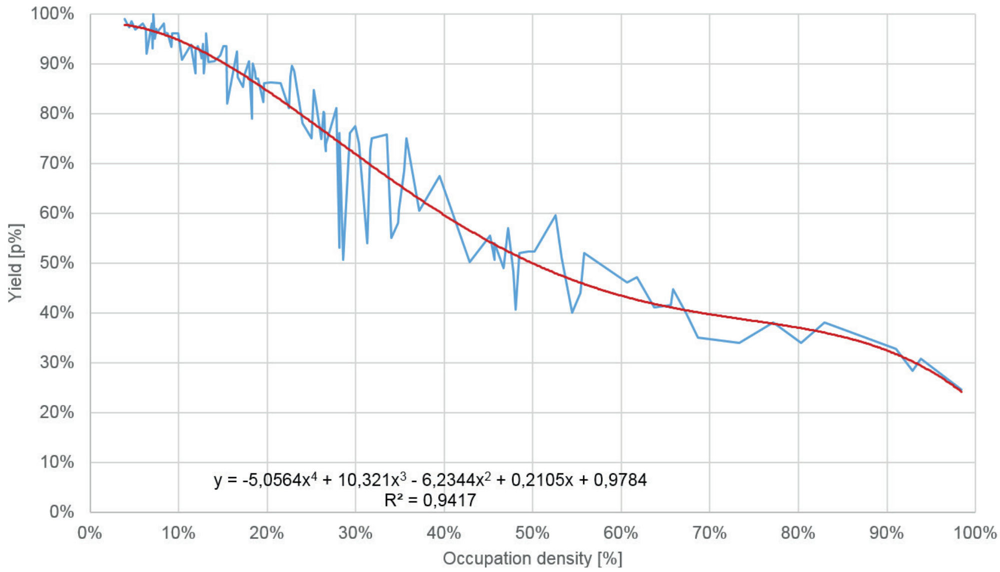

FIGURE 6: Average effect of occupation density on yield - occupation density < 100%.

The highest number of misclassifications was recorded for the quite balanced mixing ratios of 60/40, 50/50 and 70/30, while the number of falsely ejected reject particles is smaller for imbalanced input compositions. In general, the slope of all graphs is much reduced at occupation densities of around 30%. This means that the absolute number of incorrectly ejected reject particles is significantly less prone to increasing with rising occupation densities if the general level is > 30%.

As a result of the exponential decrease of recovery and the concave increase of the number of falsely ejected reject particles, a linear decrease of purity in the eject fractions can be observed for increasing occupation densities (see Figure 8, right). With decreasing eject content in the input, the decline of eject purity worsens.

A tendency to greater volatility can be observed for the input material if the content of eject particles is small. This trend is consistent with the sample size used for all experiments. For input samples with low contents of eject particles, even small numbers of falsely ejected reject particles constitute quite large amounts of impurities in the eject fraction. Fluctuations of the absolute numbers of incorrectly ejected reject particles therefore rather affect the graphs of input samples with high content of reject particles than vice versa.

Figure 8 shows that, as eject content of the input of a sorting stage increases, the slope of the resulting linear graph softens. While the negative gradient of the linear functions in principle increases with the reject content in the input, the magnitude of this change is not consistent. The graphs of the input samples 70/30 and 60/40 display an anomaly concerning the otherwise consistently increasing negative gradient of the linear graphs.

3.5 Economic Potential

This paper highlights the effects of input composition and throughput rate on recovery/product quantity, yield, and purity of the eject fraction from SBS stages. Better

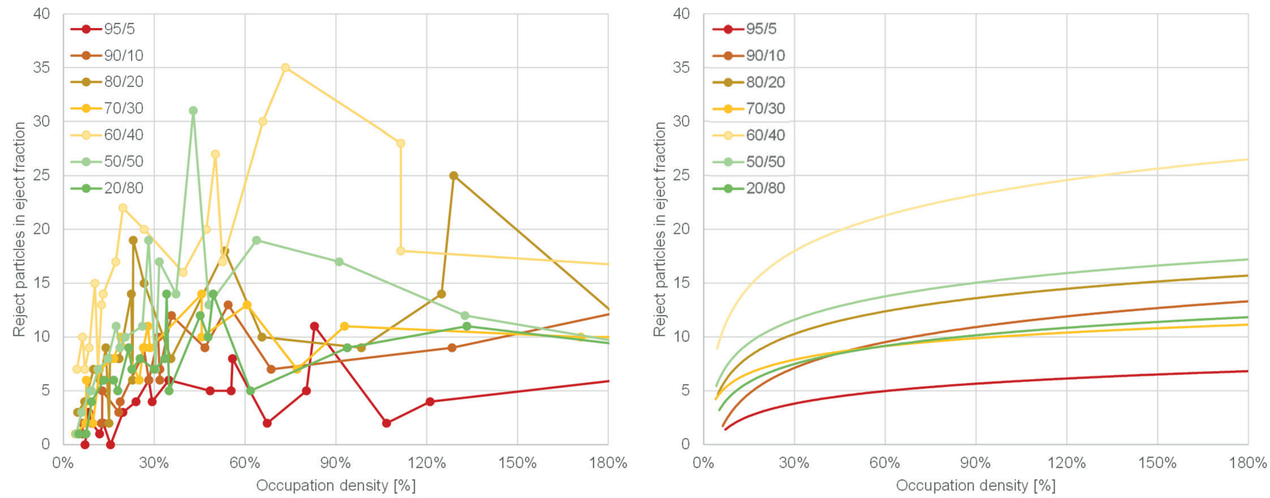

FIGURE 7: Influence of occupation density on the ejection of reject particles for different input compositions (left: raw data, right: mathematical fit) – occupation density < 180%.

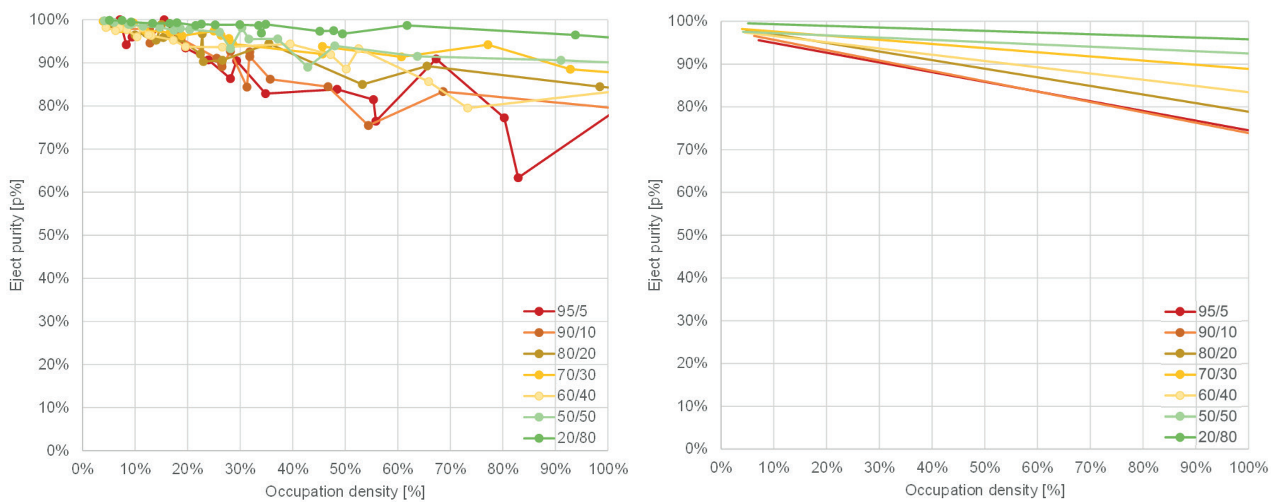

FIGURE 8: Effects of occupation density on eject purity for different input (left: raw data; right: mathematical fit) compositions – occupation density < 100%.

knowledge of the interdependence of these variables was also acquired.

When the accuracy of sensory detection and mechanical efficiency is known, both datasets can be combined to assess the efficiency of SBS steps. Each input composition imposes an upper limit on the achievable recovery, the yield, and purity. This upper limit cannot be raised by changes to the experimental setup, say, be applying a better sensor, since it is a function only of the ratio of eject to reject particles in the input stream.

To demonstrate the value of the ascertained results, Figure 9 shows a simplified sample application. The graphs (yellow= yield, red=eject purity and green=product quantity) are displayed for a certain input composition.

It was assumed that the eject fraction, produced during this exemplary sorting stage, can be sold for different prices (100/80/60 €/t), depending on its purity (95/90/85 wt%) achieved by sorting. For simplification purposes, assume that the mass balance is in accordance with particle related composition.

Purity, quantity, and possible losses of the potential product must be considered to find out at which occupation density (throughput rate) the highest profit per hour is made. For every input material whose sorting step can be described with the graphs shown in Figure 9, the price and quality of the respective maximum product quantity can therefore be located at the secondary axis of Figure 9 (green arrows). In Table 4, the best occupation densities for meeting the quality requirements are given, including the corresponding product price, yield, product quantity and arising profit per hour.

Evidently, the highest obtainable profit is found at an occupation density of 44 %, even though the generated product quantity is highest at an occupation density of 67% and the highest yield would be generated at an occupation density of 23%. Therefore, knowing the interdependencies of the described factors may help optimizing a sorting stage in the first place.

4. CONCLUSIONS

Evaluating the efficiency of an SBS machine without running sorting experiments, depends on a multitude of influencing factors. These factors can be divided into two categories that do not influence each other:

- Factors affecting the functionality of built-in sensors, reducing the content of particles that can be detected, recognised, and classified;
- Factors related to mechanical discharge issues, reducing the efficiency of an SBS machine independent of the accuracy and suitability of built-in sensors.

The scientific results shown here provide a basis for assessing the efficiency of SBS units in sorting plants. Displayed data comprises the predominant influencing factors (input composition and occupation density) affecting mechanical discharge issues.

When combined with the sensor-specific efficiency (depending on what a sensor is used for), these data can be used to predict the efficiency of a machine and maybe even the efficiency of many connected SBS machines.

The influence of input composition and throughput rate on sorting efficiency has been established using model mixtures sorted in an experimental setup at various throughput rates. The following main conclusions are based on the experimental series run with homogeneously shaped particles, evenly distributed particle weights and uniform particle size for eject and reject particles:

- Input composition does not affect the yield for any throughput rate/occupation density.
- With increasing occupation density/throughput rate, the yield decreases exponentially from approx. 98 p% to approx. 10 p%.
- The average yield, a function of the occupation density/throughput rate, can be shown as a polynomial function of the fourth degree for occupation densities <100% (Figure 6).

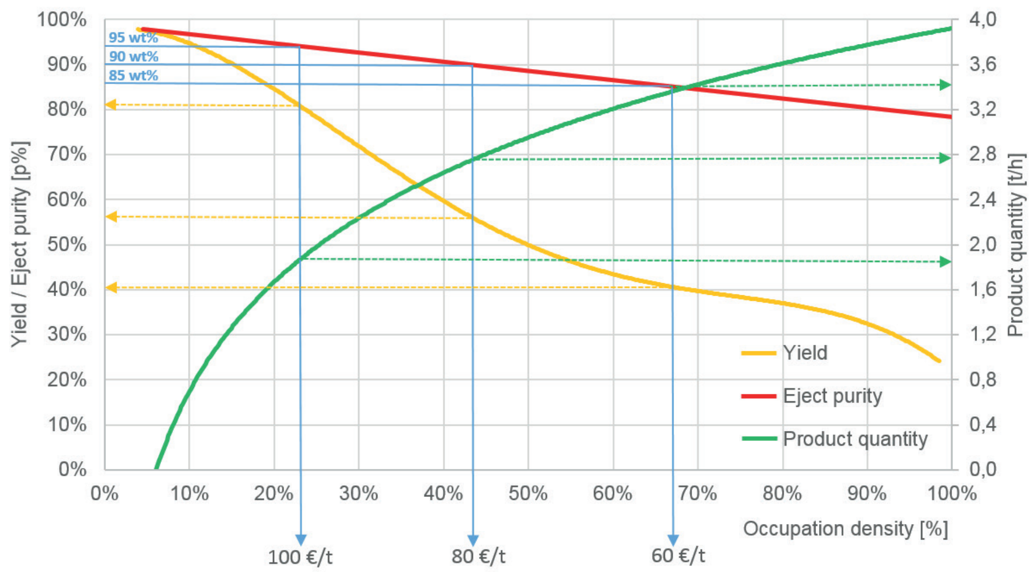

FIGURE 9: Graphs of yield (yellow), eject purity (red) and product quantity (green) for a sample case; blue arrows – material value for a specific quality; yellow arrows – obtainable yield for a specific eject purity; green arrow – obtainable product quantity for a specific eject purity.

TABLE 4: Profit per hour with respective process and product parameters.

Occupation density	Quality requirement	Product price	Yield	Product quantity	Profit
23%	95 wt%	100 €/t	81 wt%	1,85 t/h	185 €/h
44%	90 wt%	80 €/t	56 wt%	2,78 t/h	222 €/h
67%	80 wt%	60 €/t	41 wt%	3,45 t/h	207 €/h

- As occupation density/throughput rate rises, product quantity increases (despite a decrease in recovery) following a saturation curve that reaches maximum for an occupation density of approx. 60% (Figure 4).
- Eject purity can be plotted as a descending linear function of occupation density/throughput rate. The slope of this function is related to the input composition.
- The higher the eject content in the input composition of an SBS stage, the smaller the slope of the related descending linear function (Figure 8).

Profounder datasets may be obtained in large scale experimental series using stable input compositions and longer test durations are advisable. Other influencing factors like grain size distribution of the input material, particle shape, and machine design should be examined to expand the dataset presented in this paper.

Actually material flows in sorting plants are subject to powerful fluctuations due to changes to the input composition and irregular material discharge of upstream processing machinery. As has been shown here, such temporarily fluctuating throughput rates can painfully reduce the sorting efficiency of SBS stages. Choosing processing machinery to regulate input rates and to discharge the output fractions regularly can enhance the performance of downstream sorting stages at the same overall throughput rate. Another option of how to reduce fluctuating input rates is using bunkers. Depending on the scope of fluctuations, the required bunker volume may vary, causing high investment costs. This approach may not be feasible for material streams like light-weight packaging waste that, due to its non-bulk properties, could generate a blockage when stored in a bunker.

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