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Full length article

Beyond sorting: using sensor-based sorter data for real-time throughput and composition monitoring

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ABSTRACT

Modern sorting plants for lightweight packaging waste (mainly plastics, metals and compounds) can operate with up to 50 sensor-based sorters (SBS), generating large volumes of material flow data. This study presents the first systematic evaluation of SBS data for real-time, inline monitoring of throughput (0.1–17.5 t/h) and input composition (eject shares 5–50%). Two fractions were examined: larger polyethylene “chips” sorted by color via visible light (VIS) cameras, and smaller “flakes” of various polymers sorted by near-infrared (NIR) technology. Formulas converting pixel counts to mass-based metrics were developed, while artificial intelligence was deliberately avoided to highlight the inherent potential of pixel data. Monitoring accuracy depended strongly on particle overlap, measured by the superposition factor (fsp). For fsp<1.05, median throughput deviations were +0.3% (chips) and −11.6% (flakes); composition deviations were +3.9% and +2.4%, respectively. If the outlined challenges are considered, the technology can be used in realistic conditions of plant operation (fsp<1.25).

1. Introduction

The global warming potential and cumulative energy demand of recycled packaging material made from plastic, steel or aluminium is lower than the impact of virgin material (Metal Packaging Europe 2022; Volk et al., 2021). Thus, there are great efforts to enhance recycling rates within but also outside the European Union. To generate recycled products from waste, three key steps are required: collection, sorting, and material recovery. Material that has been littered is lost for the recycling chain. Similarly, in the sorting stage, recyclable materials that are not successfully separated end up in incineration instead of reaching the material recovery level. This outlines the importance of improving collection schemes, sorting technology and plant performance to maximize resource recovery (Pomberger 2020).

Lightweight packaging waste sorting plants (LWP plants) are a specific type of material recovery facilities (MRFs) or “sorting centers”. Their primary objective is to separate mixed packaging waste of the so-called “lightweight packaging” to create various categories of recyclables, like polyethylene (PE), polypropylene (PP), polyethylene terephthalate (PET), beverage cartons (BC), ferrous metals (Fe) and non-ferrous metals like aluminum (NE), besides others (Antonopoulos et al. 2021, Stadler Anlagenbau 2025a). “Lightweight packaging” refers to packaging materials composed predominantly, but not exclusively, of plastics, metals, and composite materials, which are collected in separate bags or bins from other waste streams (e.g. in Austria, Germany or Spain). They do not include heavier packaging like glass bottles (European Environment Agency, 2025). To improve both the amount and quality of generated recyclable fractions in LWP plants an increasing number of sensor-based sorters (SBS) is used. Modern LWP plants operate with up to fifty SBS, mainly using near-infrared (NIR) technology to separate different types of plastics as well as beverage cartons and paper (Kusch et al., 2021; Küppers et al. 2022). Some fractions are further separated by colour (e.g. Polyethylene terephthalate (PET): blue, green, clear, etc.) using SBS based on the visible spectrum of light (VIS). Depending on the waste management structure of a country, this can happen directly in the LWP plant as unshredded objects and/or in a subsequent processing plant as flakes (Lubongo et al. 2024; Wahab et al. 2006).

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The sensor data created from those SBS was not used for sensor-based material flow monitoring (SBMM) or plant control in the past (Kroell et al. 2022; Curtis et al. 2021). With the rising awareness for the potential of digitalization in the waste management sector, there is a trend to collect and store all kinds of data in LWP sorting plants. The long-term vision is to use this data not only for first level support but also for (automated) plant optimization. In preparation for this, SBS data is currently being stored in many sorting plants, without a specific use case or need. Depending on the storage method, this requires considerable storage capacity for long-term monitoring: When storing the raw data of a hyperspectral NIR-camera at an acquisition rate of 300 frames per second about 137 GB/h is generated, assuming all spectral channels are recorded by the SBS (Maghmoumi et al. 2025). In contrast, if classified pixel data with the respective time stamp and position on the conveyor belt is stored as comma-separated values (CSV) the required storage quantity is reduced to 1 GB/h. Using an optimized storage format (e.g. parquet), this can further be reduced to 20 MB/h (Kamleiter, 2023). For most applications an aggregation to 1-minute-values might be sufficient, which further decreases storage demand (Schlögl et al. 2024). By following this approach, the supplier TOMRA reduces the storage demand of one SBS to 700 – 900 per month while processing up to five billion data points per day from multiple SBS using Azure Data Explorer (ADX) analytics (TOMRA Recycling, 2022a, 2022b).

The acquired data is often stored in cloud systems and is criticized of potentially being so-called "digital waste". Digital waste is data which is not used, yet it causes avoidable energy consumption through necessary power supply and cooling of servers (Gäth 2022). Therefore, not all available data should be stored and even useful data might not be needed in the highest possible resolution. An assessment on the importance of specific parameters is necessary to define what data streams are usable for specific use cases and if an aggregation of the data is possible to reduce the required storage capacity (Schlögl et al. 2024).

To the best of our knowledge there have not been publications outside of this research project concerning the systematic evaluation of the potential of SBS data for plant optimization, the challenges of the implementation of such systems and relevant parameters within SBS data sets for the implementation. The premises for the presented study are based on research using “external sensors”, which have to be purchased in addition to sensors already existing within the SBS. There have been multiple studies investigating the use of data of different types of external sensors (NIR, VIS, volume flow sensors, etc.), which are mounted over conveyer belts to obtain data with fully known conditions (e.g. Chen et al. 2023; Feil et al. 2019; Hernández Parrodi 2021; Kandlbauer et al. 2021; Küppers et al. 2022; Kroell 2023; Roming et al. 2023; Schlögl et al. 2022b). Alongside those research approaches, several commercial monitoring solutions have emerged: On the one hand, there are products using sensors mounted directly on conveyor belts in sorting plants (e.g., EVK Monitoring, EverestLabs, greyparrot, PolyPerception, StadlerConnect). On the other hand, there are manufacturers offering dedicated machines for material flow characterization (e.g. EagleVizion, RTT Flakeanalyser, Sesotec,). These systems typically analyze shredded material, either inline within the material stream or separately from the sorting line for quality control purposes (EVK 2025; EverestLabs 2025; Greyparrot 2024; PolyPerception 2025; RTT 2025, Sesotec, 2025, Stadler Anlagenbau 2025b).

While such systems can provide valuable insights in material flow characteristics, they entail extra investment and risk generating avoidable “digital waste” if the same information could be extracted from existing SBS sensors (“internal sensor data”). We want to emphasize that plants of the future will likely use a combination of internal and external sensor data, as the SBS data can only be collected where SBSs are positioned in the plant. An example of the effective use of additional sensors would be to place them before the baler. This underlines both the value of ongoing monitoring product development and the potential benefits of leveraging already installed SBS infrastructure.

These studies and products show that sensor data can indeed be used for monitoring material flow characteristics. Nevertheless, they do not investigate the challenges when using built-in sensors of SBS. These challenges result from the fact that the primary purpose remains sorting and not the analysis of material flow properties. Data of SBS is based on teach-ins and sorting algorithms, which are built for obtaining the best sorting results. However, this might impair the quality of data for monitoring purposes: One example for a consequence of pre-processing is weighting certain material classes to enhance the ejection of the target fraction. For example, weighting is set from 1 to 2 for PET pixels, every PET pixel will be counted twice. The advantage is that it makes it easy to quickly influence the sorting results, without changing the teach-in or the set-up. The disadvantage is, that it results in an overrepresentation of these material classes when using the data for SBMM. Furthermore, the type of algorithm for ejection can affect the gathered data: With object-based ejection, a bottle consisting of a PET body, a multilayer label, and a polyethylene cap, might be classified as 100 % PET to ensure targeting the whole object for ejection. If these influencing parameters remain unidentified and the data is only accessible in pre-processed form, this is a constraint on the use and interpretation of SBS data both with and without the use of machine learning (Schlögl et al. 2022a; Schlögl et al. 2023; Schlögl et al. 2024).

This paper examines whether SBS data can be used for monitoring the most relevant material flow metrics in LWP plants: throughput and material composition. These parameters have been investigated systematically in sensor-based sorting trials by Küppers et al. (2020a, 2020b). However, the VIS and NIR data generated during the sorting processes has not been analysed yet. The data includes results of two different test conditions:

(1) VIS cameras for sorting Low-Density-Polyethylen (LDPE) chips by colour (red, white)
(2) NIR cameras for sorting flakes by material (Polyolefins (PO) and PET).

The innovative approach of the presented study is to use this inline SBS data for sensor-based material flow monitoring (SBMM) and examine its potential for automated sensor-based plant control tackling the challenges of using data which was not optimized for the purpose of monitoring. Although the material analysed was smaller than typical lightweight packaging waste due to the limitations of the experimental setup, the findings remain relevant for real waste sorting plants because the central question investigated is whether pixel data captured by sensor-based sorters during the sorting process can be effectively utilized for material flow monitoring. It is beneficial that the authors of this study have created the teach-ins of the presented sorting experiments and can therefore interpret the impairing factors on the data. The following research questions (RQs) are addressed within this study:

RQ I: Is the monitoring of throughput possible for both test conditions?
RQ II: Is the monitoring of input composition possible for both test conditions?
RQ III: Are the results affected by the level of superposition caused by higher throughputs?

2. Material and methods

To access the accuracy and reliability of SBMM based on data created during a sorting task a thorough analysis was conducted within this study. The used data for this analysis originates from sorting experiments with different input material and sensor technology to evaluate whether SBMM based on SBS data is possible under different conditions. Those sorting experiments were conducted with a combination of different throughputs and material compositions. The generated data of both sorting tasks was not altered before doing the presented analysis.

2.1. Material

2.1.1. Experiments were conducted with mixtures of two types of materials

1. Chips: LDPE red and LDPE white
2. Flakes: PO and PET

The chip material (see Fig. 1a) was custom-made for the sorting experiments of Küppers et al. (2020a, 2020b) and thus only differed in colour (red/white). The flake material (see Fig. 1b) was a processed LPW shredder fraction, only consisting of PO and PET. The chips are on average of bigger particle size (approx. 30 × 60 mm) and higher thickness (3.1 – 3.5 mm), while flakes are smaller (< 30 mm) and thinner (0.2 – 2.8 mm), with a higher variation in dimensions due to the shredding process. For each sorting experiment with chips exactly 1 000 particles with a total mass of approx. 4.85 kg were used. More particles were used in the experiments with flakes: Between 18 500 and 34 500, depending on the generated input composition. This was not constant, as more PET material was added to the mixture to create higher shares of PET material. The resulting input mass of the flake material was ranging from 5.95 – 11.04 kg.

With each material different mixtures were created, representing specific input compositions and therefore possible effects of differing eject shares. In this context, eject refers to the material fraction that represents the target fraction of the sorting process (Therefore, all material supposed to end up in the eject container (See Fig. 1c), if sorting was faultlessly). In the first set of trials LDPE was sorted by colour, in which white particles were defined as eject, while red particles were defined as drop. In the second set of trials PET flakes were defined as eject, while PO flakes were drop. Six different mixing ratios were created for each set of trials: The generated eject shares in the input material were 5 %, 10 %, 20 %, 30 %, 40 % and 50 %. The notation of the mixtures in this paper is "Drop/Eject". Thus, in a mixing ratio of 95/5 the dominant proportion is drop (95 % LDPE_red or PO) and the smaller proportion is eject (5 % LDPE_white or PET). It is important to note, that this designation does not describe the outcome of the sorting process, but the input composition. The sorting results are not relevant in this context, as this paper evaluates the accuracy of monitoring the material flow characteristics (e.g. material shares) using data generated during the sorting process.

2.2. Methods

The experiments were conducted on a set-up consisting of a feeding hopper, a vibrating conveyor and chute sorter with a working width and length of 500 × 455 mm (see Fig. 1c). In the first set of trials the chip material was sorted by colour using a linescan VIS camera (AViiVA SC2, teledyne e2v) with an image resolution of 1365 × 1 px and a spectral response of 400 – 700 nm. In the second set of trials the flake material was sorted based on the type of material using a hyperspectral NIR camera (EVK Helios NIR G2–320, EVK DI Kerschhaggl GmbH) with an image resolution of 312 × 1 px and a spectral response of 1000 – 1700 nm.

For both materials similar sorting experiments were conducted with different input compositions (5 – 50 % eject shares) and varying throughput rates (Chips: 0.3 – 17.5 t/h; flakes: 0.1 – 5.4 t/h). First, a material mixture with a certain input composition was created and the masses of the components were documented. Second, the mixture was sorted by discharging the eject fractions. Third, the data generated during the sorting process was exported. This data included the number of pixels per material class (eject, drop, not classified (NC) and background) and the trial time. Both output fractions were then mixed and used again for the next sorting trial with the same input composition at a different throughput rate. After sorting this input mixture at different throughput rates another mixture with a different eject share was created. In total 109 experiments with chip material and 63 experiments with flake material were analysed in this study.

The basis for using SBS data for SBMM is correct classification, which was ensured in preliminary tests. The teach-ins were created with a focus on optimal differentiation between eject and drop, as this is the priority of a SBS. More details on the methodologies for the sorting tasks can be gathered from Küppers et al. (2020a) for flake material and Küppers et al. (2020b) for chip material.

2.3. Data analysis

To evaluate the potential of using SBS data for monitoring the acquired data was analysed regarding inherent information on two key characteristics: throughput and input composition. The correlation between pixel data and those characteristics depends on the monitoring conditions (e.g. camera setup and characteristics of material flow), thus different approaches are presented for the investigated scenarios.

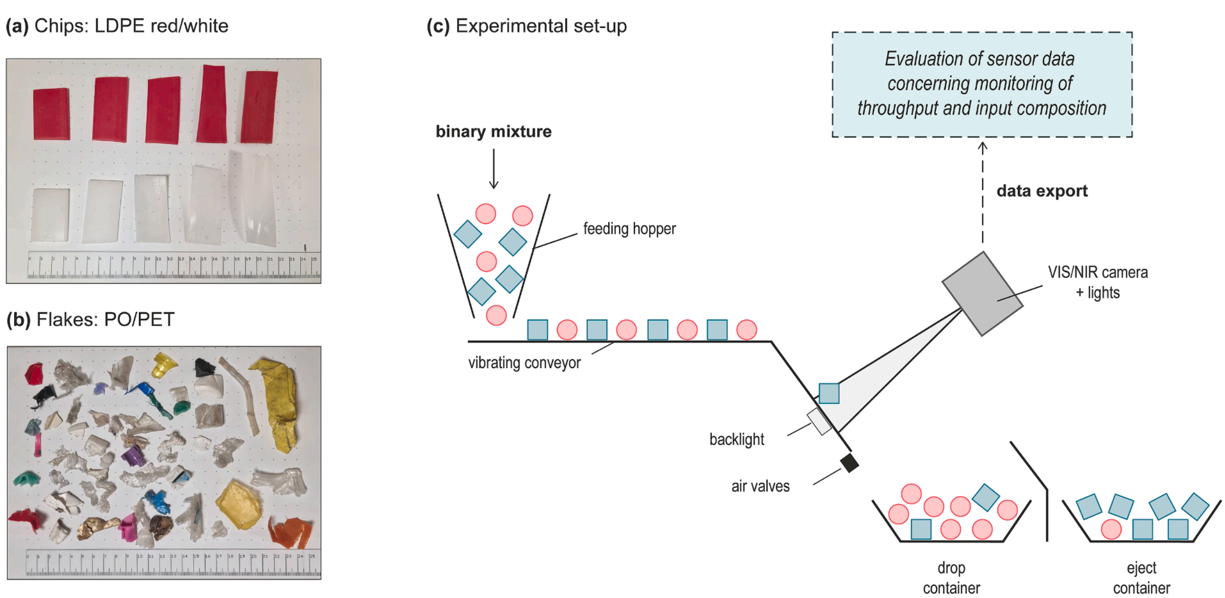

Fig. 1. Materials and Experimental set-up. (a) Chips: LDPE red/white (using VIS camera), (b) Flakes: PO/PET (using NIR camera), (c) Scheme of experimental set-up using a chute sorter with VIS and NIR camera and correspoding light sources.

Concerning the monitoring of sensor-based throughput the ground truth was the mass-based throughput (tp_{mb}), calculated as the ratio of input mass and trial time (see Eq. (1)).

$$tp_{mb} = \frac{m_{input}}{t} \tag{1}$$

To visualize the influence of overlapping particles on the calculation of pixel-based throughput, as well as pixel-based eject shares, a new parameter was introduced: The superposition factor (f_{sp}). It is the ratio of the measured pixels per trial ($\sum px_i$) and the maximum number of pixels of a material mixture ($\sum px_{max}$), which was measured during very low throughputs, resulting in no overlapping of particles ("perfect singularisation"). Thus, it quantifies the average superposition of particles during a trial. A value of f_{sp}=2.0 represents on average two pixels of the particles being on top of each other (See Fig. 2). The optimum in plant operation would be f_{sp}=1, realistically values of f_{sp}=1–1.25 are aimed for. Values greater than f_{sp}=1.5 are not suitable for a sorting process, as the severe overlap hinders both detection and ejection of particles.

$$f_{sp} = \frac{\sum px_i}{\sum px_{max}} \tag{2}$$

The sensor-based throughput was calculated by converting the detected pixels per time using a correlation formula. This correlation formula depends on both the input material and the detection system used (sensor, algorithm, etc.) and was determined iteratively with the aim of minimising the difference between sensor-based and mass-based throughput. The sensor-based throughput (tp_{sb}) of chips was calculated according to Eq. (3), while for flakes according to Eq. (4). The relative deviation concerning throughput monitoring (RD_{tp}) was calculated in relation to the ground truth (See Eq. (5)).

$$tp_{sb,\ chips} = \frac{\sum px}{t} * \left(1 + 2.8 * \frac{\sum px_{NC}}{\sum px}\right) * \frac{1}{360\ 000} \tag{3}$$

$$tp_{sb,\ flakes} = 0.00109 * \frac{\sum px}{t} + \left(\frac{\sum px}{t} * \frac{1}{170\ 000}\right)^3 \tag{4}$$

$$RD_{tp} = \frac{tp_{sb} - tp_{mb}}{tp_{mb}} \tag{5}$$

A pixel is detected as NC, if the spectra neither fits the requirements of the material classes of eject or drop. The share of NC is given according to Eq. (6):

$$c_{NC,total} = \frac{\sum px_{NC}}{\sum px} \tag{6}$$

For the analysis of sensor-based monitoring of eject shares the ground truth was the manually generated eject shares (c_{eject}; 5 – 50 %). These were compared to the pixel-based eject shares (c_{sb}) calculated by the number of pixels of eject and drop gathered during one trial (See Eq. (7) and Eq (8)). As the relative deviation concerning monitoring of eject shares ($RD_{c_{eject}}$) was too high, a material specific correction formula was determined iteratively to improve the results. The resulting formula for chips is presented in Eq. (9) and for flakes in Eq. (10). The resulting relative deviation concerning eject shares ($RD_{c,\ eject}$) was calculated in relation to the ground truth c_{eject} (See Eq. (11)).

$$c_{sb,\ chips} = \frac{\sum px_{white}}{\sum px_{white} + \sum px_{red}} \tag{7}$$

$$c_{sb,\ flakes} = \frac{\sum px_{PET}}{\sum px_{PET} + \sum px_{PO}} \tag{8}$$

$$c_{sb,chips_{corr}} = c_{sb,\ chips} * \left(1 + \frac{\sum px}{t} * \frac{1}{1\ 900\ 000}\right) \tag{9}$$

$$c_{sb,flakes_{corr}} = c_{sb,\ chips} + \frac{\sum px}{t} * \frac{0.8}{50\ 000\ 000} \tag{10}$$

$$RD_{c_{eject}} = \frac{c_{sb} - c_{eject}}{c_{eject}} \tag{11}$$

3. Results and discussion

The data recorded during the sorting trials was analysed for its suitability for SBMM. Two key parameters were monitored: the throughput of each trial and the respective eject fraction in the mixture.

3.1. Monitoring of throughput

The hypothesis "the mass-based throughput can be determined by the level of overlapping of particles, which is detected by sensors" was made for the evaluation of throughput monitoring. Thus, a higher throughput results in more superposition than a lower throughput. The data presented in Fig. 3 confirms this assumption for both test series, as they always show a positive correlation between mass-based throughput and pixel-based superposition factor. Within one test series, neither for the flake material nor for the chip material a systematic dependency on the mixing ratio (e.g. "95/5": 95 % eject, 5 % drop) can be seen. Rather, both materials show overlapping areas of the 95 % confidence bands, in particular in the range which is of relevance for applications in LWP sorting plants (f_{sp}=1–1.5). This leads to the conclusion that the superposition factor is a suitable reference parameter, regardless of the different conditions in both test series. These differences include different cameras (different sensors, framerates, algorithms, etc.) and different input compositions (differences of material, bulk density, particle size and thickness, shape, etc.).

A relevant detail is noticeable in the marked areas of the zoomed sections in the graphs: At f_{sp}=1, which represents a singularisation of 100 %, the range of mass-based throughput values of the chip material (Fig. 3a) is about double of those of the flake material (Fig. 3b). Overall, higher values for throughput and superposition factor occurred within the chip material. This can be explained by the larger thickness of the chips, as the same occupied area results in a higher weight if the material is thicker.

For the realisation of sensor-based throughput monitoring, the collected pixel data (px/h) of each trial was converted to t/h by using a correlation formula (Eq. (3) and Eq. (4)). In Fig. 4 the accuracy of the mass-based throughput (=ground truth) compared to the resulting sensor-based throughput for both test series is presented. Fig. 4a shows a high correlation between mass-based and sensor-based throughput. Within the zoomed section (0 – 2 t/h) a trend of slight underestimation of the model for flakes (PO/PET) is visible, whereas the data points for chips (Red/White) are close to the diagonal. For higher throughputs, starting at about 2.5 t/h, flakes present opposite behaviour: The throughput is systematically slightly overestimated. To further investigate these effects, the relative deviation (see Eq. (5)) between the actual

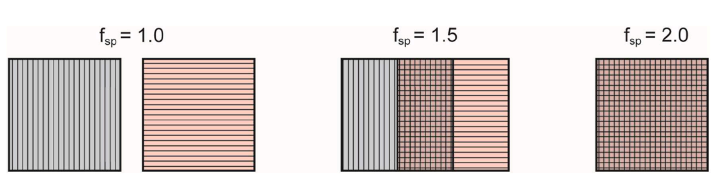

Fig. 2. Visualisation of different superposition factors by the example of two particles with the same number of pixels.

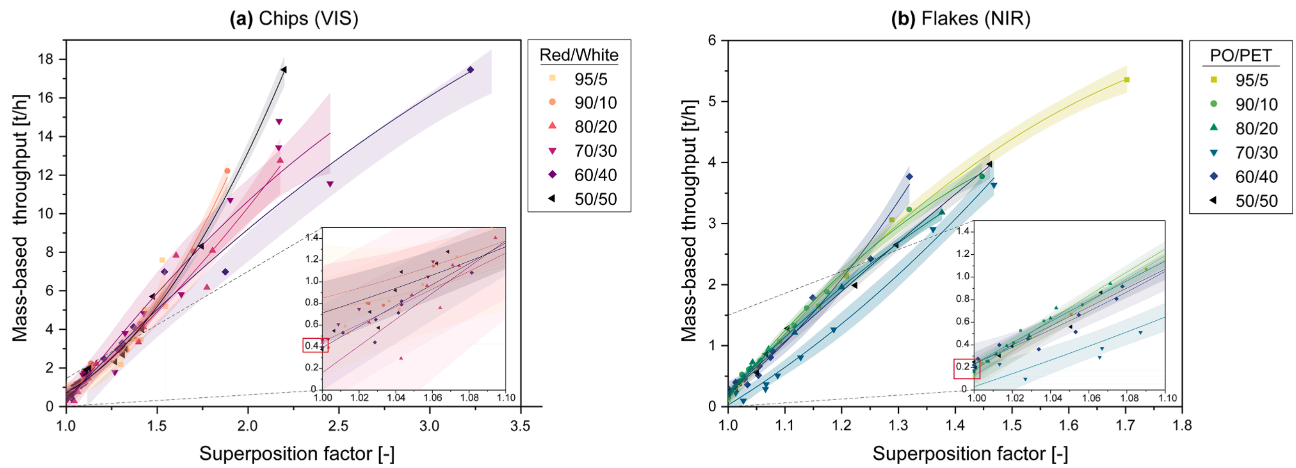

Fig. 3. Correlation between mass-based throughput [t/h] and pixel-based superposition factor [-] for (a) Chips (LDPE Red/White; VIS) and (b) Flakes (PO/PET; NIR). Presented with fitting curves of second order and 95 % confidence band. Data points of f_{sp}=1 marked in red box in associated zoomed sections.

mass-based throughput and the calculated sensor-based throughput in relation to the superposition factor is presented in Fig. 4b and 4c. While the chip material is less affected by the level of superposition (apart from the outlier at $f_{sp} = 3.22$), both visualisations show the described effects for flakes: Low superposition results in underestimation, high superposition results in overestimation.

Nevertheless, for ideal singularisation and therefore low superpositions (f_{sp}<1.05) the relative deviation for both chip and flake material is within a small range (Chips: 10.3pp and flakes: 9.1pp, with pp abbreviating "percentage points") for all mixing ratios. This indicates a good reliability of the model over a wide range of material compositions at good singularisation. For trials with frequent superpositions (f_{sp}>1.25) the calculated values had higher fluctuation (Chips: 26.7pp and flakes: 28.8pp). However, since the aim in plant operation is to achieve good singularisation before sensor-based sorters, these extreme cases of very frequent superposition are rare and therefore less relevant for the evaluation of the potential of SBS data.

For f_{sp}<1.05 the median of the deviation between mass-based and sensor-based throughput is +0.3 % for chips and −11.6 % for flakes (See Fig. 4c). This indicates an optimising potential for monitoring flake material. As visualised in Fig. 4b, both test series follow an almost linear trend within the target range for plant applications (fsp < 1.25). This indicates that the accuracy of sensor-based throughput monitoring could further be improved through linear regression, if needed for the respective use case. Notably, even without applying machine learning, the underlying pixel data already provide meaningful results (see Fig. 4a). This demonstrates that pixel-based monitoring offers a straightforward and practical solution for throughput monitoring using the built-in VIS or NIR sensors of SBS in LWP sorting plants

3.2. Monitoring of input composition

The hypothesis "An increase in superposition leads to a decline in results" was made for the accuracy assessment of input composition monitoring. The reasoning for this theory is the obvious effect of missing information due to covered material pixels which thus either cannot be detected or are misclassified due to mixed spectra. During evaluation of the sensor data, another influential factor was noticed: The quantity of detected pixels of the material class "not classified (NC)" depends on the superposition and therefore on the throughput. In Fig. 5 the correlation between superposition factor and NC pixels is presented. As in the former presented results, the highest values for the superposition factor (x-axis) of the chip material are significantly higher than those for the flake material, due to material properties.

The two materials demonstrate a clear difference regarding the NC behaviour. The chip material shows an increase of NC pixels at increasing superposition factor both in absolute pixel numbers and in relative pixel shares. On the contrary, the corresponding graph for the flake material (Fig. 5b) shows a decrease of NC pixels. Apart from the curve shapes, the results of the analysis differ in the amount of the occurring NC pixels as well: Fewer pixels were classified as NC for the flake material. The highest values are 1 680 869 px for chips but only 41 084 px for flakes. Correspondingly, regarding the shares the highest values are 79 % for chips and 0.2 % for flakes.

There are multiple reasons for this behaviour: Since the chips are quite thick, they are not in the optimal focus area of the VIS camera when overlaid, which degrades detection and enhances the chance for classification as NC. In addition, the particles are no longer aligned at the right angle to the camera when partially overlapping, which can further negatively affect the refraction of light, resulting in misclassification. For the flake material - classified with a NIR camera - the superposition appears to have a positive effect. We propose the following hypothesis to explain this behaviour: PET particles are transparent and are therefore usually classified partially as background when the material is thin (due to transmitted and thus lost radiation) or as NC (due to reflection at shiny spots). In case of superposition, a mixed spectrum of PET and PO is scattered back when PET particles are on top. With the used teach-in these mixed spectra are classified either as PET or PO. Therefore, although the total number of detected pixels is reduced, for certain areas the detection can be improved by the superposition, as less pixels are misclassified as background. The problem with shiny spots is reduced if a PET particle is located below a PO particle. In this case, only PO is detected and problems with the detection of PET are thus irrelevant (Note: The corresponding PET pixels are not detected in this case, thus not represented in the pixel data). The detailed effects of superposition are complex, depending on material properties, camera, algorithm, and teach-in.

The results lead to the conclusion, that the accuracy of monitoring the input composition of chip material is strongly dependent on the superposition and thus on the throughput. This finding could be used for monitoring input material with similar behaviour: Higher shares of NC pixels represent higher throughput. For flake material however, the misclassification as NC caused by superposition is negligible. Therefore, the use of that parameter for SBMM is not suitable. This comparison shows an important finding for full-scale implementation of SBMM: Simple monitoring parameters can be found for different use cases, but these parameters cannot be applied without restrictions to all other use cases. An individual assessment of suitable parameters is necessary.

In Fig. 6 the accuracy of monitoring the eject shares (Chips: LDPE_white share, flakes: PET share) using SBS data is visualised. Larger

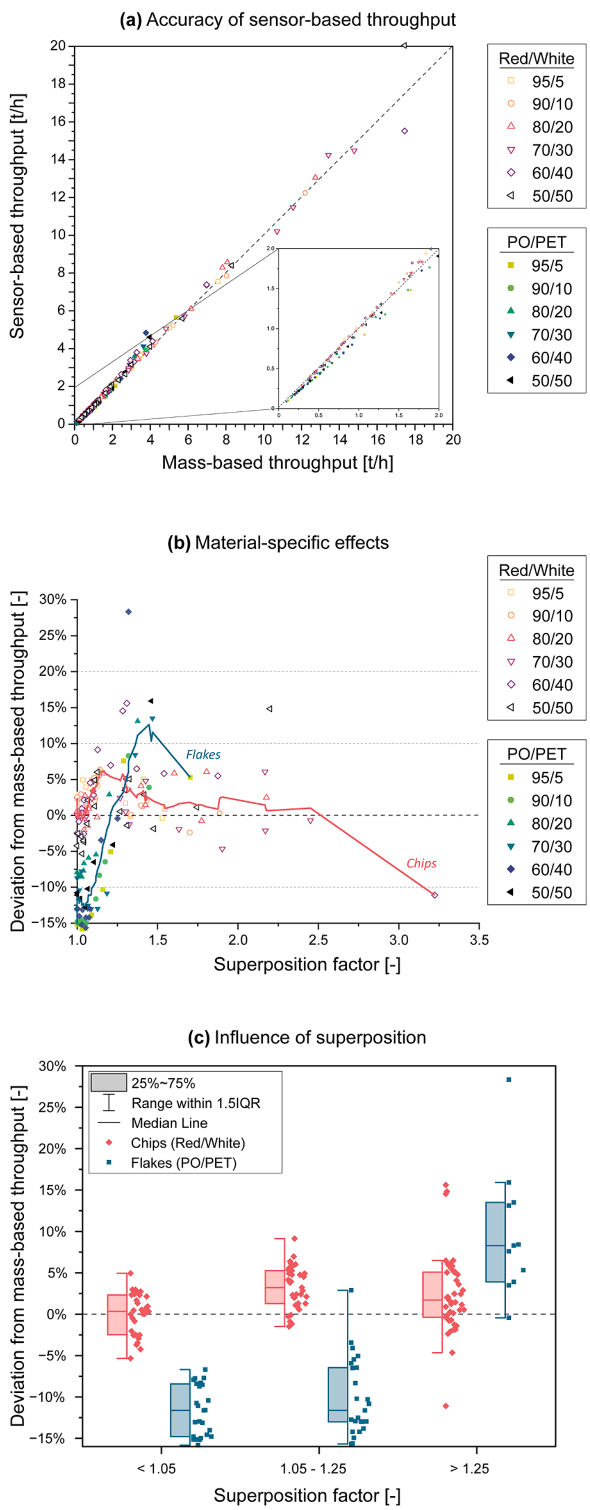

Fig. 4. Comparison of mass-based throughput and sensor-based calculated throughput. (a) Accuracy visualised as scatter plot, (b) Average deviation from mass-based throughput depending on superposition visualised with line plot of adjacent-averaging over 10 data points, (c) Associated Box-Whisker plots for f_{sp}<1.05, 1.05–1.25 and > 1.25; Red: Chips (LDPE Red/White; VIS), Blue: Flakes (PO/PET; NIR).

coloured areas in the graphs correspond to a higher difference between sensor-based and mass-based values. There are two main influential factors which have been investigated: different throughputs and different input compositions, both resulting in different superposition factors. The black horizontal lines in Fig. 6–1 show the mass-based eject shares (From 5 % to 50 %), representing the ground truth. In Fig. 6–1a and 1c the presented data is not altered. In the corresponding graphs on the right (1b and 1d) a correction formula (see Eq. (9) and Eq. (10)) is used to counteract the distortion due to overlapping of particles with higher f_{sp} values.

For the chip material the negative influence of superposition described above can be clearly seen in the original data (Fig. 6–1a). In all mixures of the chip material the measured value at high superposition factors is only about half the target value. For example, with the 50/50 mixture, the largest difference between the target value (50 %) and the measured value is 25.4pp. In comparison the monitoring of flake material (Fig. 6–1c) was more accurate even with the original data. Nevertheless, a systematic underestimation of the eject quantity can also be observed here. A plausible explanation for this phenomenon is, that the mixed spectra detected when PET particles are on top of PO particles is likely classified as PO. Further, PO on top of PET is also detected as PO. Therefore an over-representation of PO in the original data occurs.

When applying the correction formulas, the sensor-based eject shares align better with target values for both materials. This is especially true for superposition factors aspired in LWP sorting plants (f_{sp}=1–1.25). For f_{sp}<1.05 the monitoring is very precice: The highest difference between the target value and the detected eject share is 1.9pp for chips and 2.3pp for flakes. Therefore, a clear distinction between different input compositions is apparent in the data and fluctuations in input composition can be detected accordingly. A possible application for this is, for example, the early detection of performance reduction or failure of upstream aggregates resulting in a change of material composition (e.g. failure of wind sifter or another SBS). A certain difference from common material shares passing a SBS could therefore be used for an alert system or hypothetically even for a plant control system.

A clear dependence on the superposition factor occurs, even after applying the correction formula (See Fig. 6–2). The influence of high superposition on the monitoring of composition is more pronounced than the influence of different mixtures. This emphasizes the importance of singularisation for accurate monitoring. An important remark arises when comparing absolute and relative deviations: Although relative deviations appear to be high, absolute deviation are always lower than 5pp for f_{sp}<1.25. It is important to acknowledge, that not all applications of monitoring require such precision. Therefore, the appropriate selection of key performance indicators (e.g. absolute or relative deviation) and corresponding limit values depending on the respective use case is of enormous importance. As mentioned before, an individual assessment of suitable parameters is necessary.

4. Conclusion

Modern LWP sorting plants are equipped with up to fifty SBS, which classify the material continuously to enable the sorting process. In the past, the generated data was neither utilized nor stored. There is currently a trend towards storing this data, although the specific applications for SBS data have not yet been systematically investigated. In this study data gathered during sorting trials with different input compositions (5 – 50 % eject share) and throughputs (0.1 – 17.5 t/h) is evaluated regarding its potential for SBMM. The benefit of using SBS data is that it is a cost-effective alternative to installing additional sensors for monitoring.

All presented trials were conducted on the same SBS, using different materials with suiting sensors and teach-ins (red and white LDPE chips: VIS camera; shredded PO and PET flakes: NIR camera). To allow the comparability of both test data sets a new parameter was introduced: the superposition factor (f_{sp}). This factor quantifies how much particles overlap on average and thus expresses negative effects of high throughput on detection.

The following findings were obtained:

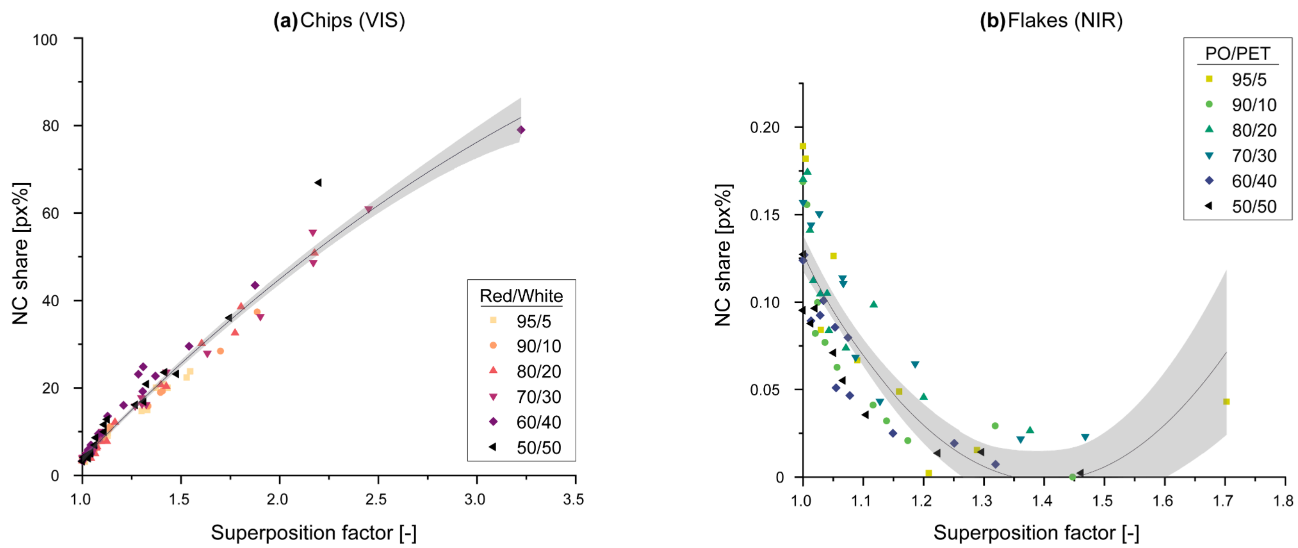

Fig. 5. Influence of superposition factor on the share of material pixels detected as "Not Classified (NC)" presented with fitting curves of second order and 95 % confidence bands. (a) Chips (LDPE Red/White; VIS), (b) Flakes (PO/PET; NIR).

- Higher throughputs result in higher superposition. Therefore, the superposition factor (f_{sp}) is a suitable parameter to visualise throughput dependent effects on SBMM, regardless of input material and mixtures.
- Throughput monitoring based on SBS data is possible, as the pixel-based throughput (px/h) correlates with the mass-based throughput (t/h). For this purpose, the pixel data was converted in mass per time unit using material specific formulas.
- The accuracy of throughput monitoring primarily depends on superposition. For $f_{sp}<1.05$ the median of deviation was $+0.3$ for chips and -11.6 % for flakes with a range of deviation always smaller than 10 %. These results could likely further be improved for the tested material by using a regression, as there is a linear correlation of deviation and superposition factor for both materials for low superpostion. But even with the simple correlation formula presented, the monitoring appears to be feasible for both materials and all mixtures in realistic scenarios with $f_{sp}<1.25$.
- Monitoring of input composition using SBS data is primarily depending on superposition as well. Three main effects of superposition have been observed:
  (1) Missing information through covered particles, e.g. transparent PET covered by non-transparent PO.
  (2) Misclassification through mixed spectra, e.g. PO covered by PET.
  (3) Misclassification as “not classified” (NC), e.g. overlapping chips resulting in up to 79 % NC share.

In examples (1) and (2) PET usually is not classified and thus underrepresented in the data.

- For chips in particular, the deviation between the sensor-based calculated eject fraction and the actual mass-based eject fraction was too high, particularly at high throughputs with $f_{sp}>1.25$: The reference value was twice the calculated value. These effects were corrected by applying a material-specific correction formula, which created results suitable for SBMM for all mixtures in both materials (Highest differences for $f_{sp}<1.25$ approx. 2pp). The resulting median deviation for fsp<1.05 was +3.9 (chips) and +2.4 (flakes). The comparison of the test series shows that whether and to what extent a correction is necessary depends on the specific use-case.
- The selection of parameters for SBMM depends strongly on the use-case as well. Even with the same test setup and procedure, different characteristic values are usable for different sensors, teach-ins and materials. For example, NC pixels were characteristic for throughput of chips material (VIS), while for flake material (NIR) this parameter was not relevant. Another example is the selection of mean value or maximum value based on either relative or absolute numbers for the assessment of eject shares: The maximum values of the relative deviation of the eject shares (using the correction formula) seemed to be high (Chips: 45 %, flakes: 27 %) and thus the data might be interpreted as being not good enough for SBMM. However, the median was always below 10 % and the absolute deviation was always lower than 5pp for $f_{sp}<1.25$. This demonstrates that an assessment based on maximum values is often not meaningful for fluctuating conditions, which are common in plant operation. Mean values are often more suitable.

The results of this study show the potential of sensor-based material flow monitoring based on SBS data. If the teach-in is suitable for the monitoring objective, irregularities of throughput and input composition can be detected for various materials and material mixtures (RQ I and RQ II). The aforementioned findings show that monitoring is affected by the degree of superposition (RQ III). However, as material on acceleration belts of SBS usually demonstrates minimal overlap, this is not a limitation under normal operating conditions.

Since teach-ins are customized for a sorting problem (type of material classes, spectral processing, definition of background, thresholds, weighing, etc.) it might be necessary for the plant operator to find individual correction formulas to make the data suitable for the respective use case. Ideally, details of the prevailing settings are known to determine these correction formulas. However, some manufacturers persist in keeping the information secret and/or do not grant access to the unprocessed data, which results in SBS operating as black boxes for SBMM. This lack of cooperation poses further challenges in practice: For example, if the teach-in is adjusted, the correction formula applied may no longer be appropriate, thus the monitoring results are impaired. To prevent a monopoly of data use by machine manufacturers, we therefore see the necessity of allowing open access to all relevant information.

The obtained results demonstrate significant potential of SBS data for various in-line analysis applications in sorting plants. First, the evaluation of up-stream sorting aggregates: This can include the detection of total failure, material abrasion, blockages, and other malfunctions. Second, if the acquired data is highly reliable: Automated or manual sensor-based process control. This can include changing the threshold of a SBS to avoid material losses or purity degradation, as well as

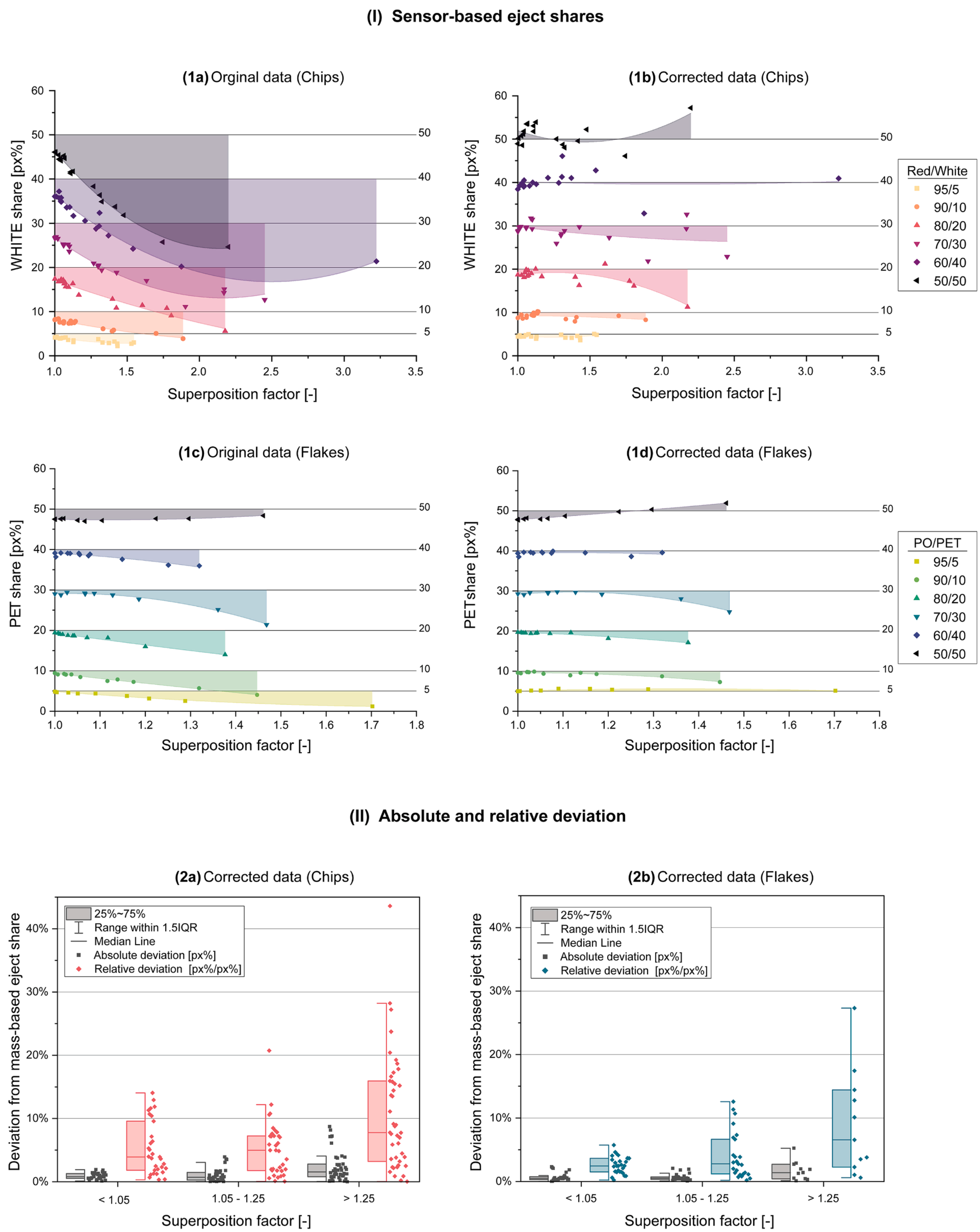

Fig. 6. Sensor-based monitoring of eject shares in input composition. (I) Sensor-based eject shares with and without the application of correction formula. Left: Original data, right: recalculated data with correction formula; top: Chips (LDPE Red/White; VIS), bottom: Flakes (PO/PET; NIR), (II) Absolute and relative deviation of corrected data from mass-based eject shares.

throughput maximization by increasing the load on the machines until the product quality limit is reached. Further, an automatic selection of teach-ins to generate different products depending on ecological or economic parameters or fluctuating input compositions. Lastly, calculation of composition of plant input by modelling the material composition reaching one or multiple SBS. This broad range of promising use-cases for SBS data are paving the way for smarter and more efficient sorting plant operations.

To further validate and extend the applicability of our findings, future studies should investigate data from different SBS in industrial sorting plants, with a focus on testing the proposed application scenarios for different materials (different mixtures as well as different polymers).

In addition, trials with unshredded packaging material should be conducted to verify that the findings are also applicable on a larger scale.

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Sabine Schlögl: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bastian Küppers:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Daniel Vollprecht:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Roland Pomberger:** Resources, Funding acquisition. **Alexia Tischberger-Aldrian:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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Data availability

Data will be made available on request.

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