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Report on the state-of-the-art and novel solutions in sorting of post-consumer plastic packaging waste

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Summary

The purpose of this report is to review the state-of-the-art in post-consumer plastic packaging waste sorting in material and plastic recovery facilities, focusing on sensor-based sorting techniques. The report outlines the current situation in Finland with regard to recycling of this waste, as well as the different routes the waste fraction takes in terms of collection, treatment, separation and sorting. Example countries with different collection and sorting schemes are also listed. Statistics on recycling performance on the EU and Finnish levels are given.

The most common sensor-based tool for plastic identification in material and plastic recovery facilities is near-infrared spectroscopy (NIR), which is integrated to sensor-based sorting units. In short, NIR utilizes the reflectance spectrum of objects to infer their chemical composition. The NIR sensor works in tandem with a separation unit, usually pneumatic air nozzles, which use compressed air to separate objects based on the spectrum. The material is presented to the sorting unit usually via a conveyor belt when sorting whole containers.

NIR has several limitations that hinder its all-around performance. Moreover, the actuation by air nozzles is imperfect, and is highly affected by the input rate of the material. Novel technological solutions leveraging different sensors with modern data-driven tools such as artificial neural networks have been studied to overcome some of these barriers. These solutions are shortly reviewed, and the levels of their technological maturity in the framework of post-consumer plastic packaging sorting evaluated.

Confidentiality	Public

Oulu 22.6.2021

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Preface

This report has been done in the public research project ALL-IN for Plastics Recycling, funded by Business Finland 2020-2022 as part of the co-innovation ecosystem with the same name. The report is part of a deliverable to task 2.3. *Enabling technologies*, and outlines the state-of-the-art survey of technological solutions related to plastic sorting, as well as their capabilities and restrictions. Moreover, novel solutions that may be used to reach gaps in the existing framework are reviewed and their technology readiness levels estimated. As an introduction, a brief overview of the recycling and sorting system in Finland as well as examples from other countries are also given.

The authors have held a workshop with the consortium partners regarding the state-of-the-art, based on which clarifications on the status quo have been updated to the document, and relevant changes have been made. The authors are grateful for the consortium for their valuable comments and improvements on the report.

Oulu 22.6.2021

Tuomas Sormunen, Sari Järvinen

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List of abbreviations

ABS	acrylonitrile butadiene styrene
AI	artificial intelligence
BFR	brominated flame retardant
CCD	charge-coupled device
CMOS	complementary metal-oxide-semiconductor
CO	carbon monoxide
CO2	carbon dioxide
DKR	Deutsche Gesellschaft für Kreislaufwirtschaft und Rohstoffe mbH
EPS	expanded polystyrene
EU	European Union
FTIR	Fourier-transform infrared spectroscopy
HDPE	high-density polyethylene
HIPS	high impact polystyrene
HSI	hyperspectral imaging
InGaAs	indium gallium arsenide
IoT	Internet-of-things
kg	kilogram
kt	kilotonne (metric)
LDPE	low-density polyethylene
LED	light-emitting diode
LIBS	laser-induced breakdown spectroscopy
LLDPE	linear low-density polyethylene
MDPE	medium-density polyethylene
MDS	magnetic density separation
MIR	mid-wavelength infrared (spectroscopy)
mm	millimeter
MRF	material recovery facility
MSW	municipal solid waste
NIR	near-infrared (spectroscopy)
nm	nanometer
PA	polyamide
PA6	polyamide 6
PC	polycarbonate
PE	polyethylene
PET	polyethylene terephthalate
PLA	polylactic acid
PLS-DA	partial least squares discriminant analysis
PMD	plastic packaging, metal packaging and drink cartons,
PMMA	poly(methyl methacrylate)
PO	polyolefin
PP	polypropylene
ppm	parts per million

PRF	plastic recovery facility
PS	polystyrene
PTFE	polytetrafluoroethylene
PU	polyurethane
PVC	polyvinyl chloride
PVDF	polyvinylidene fluoride
RDF	refuse-derived fuel
RFID	radio-frequency identification
RGB	red, green, blue (colour model)
RoAF	Romerike Avfallsforedling IKS
SME	small and medium-sized enterprises
SWIR	short-wavelength infrared
TRL	technology readiness level
UV	ultraviolet
WEEE	waste electrical and electronic equipment
VIS	visible (spectroscopy)
XRF	X-ray fluorescence (spectroscopy)

1. Introduction

Around the world, the consumption of plastics is steadily rising. In 2018, according to PlasticsEurope (PlasticsEurope, 2019a), the total demand for plastics in Europe (EU28 + NO/CH) was 51.2 megatonnes, of which 39.9% (20.4 Mt) was for packaging among all segments; for example, plastic for building and construction, the second largest segment, had a demand of 19.8%. As such, the target (Europarl News, 2017) by the European Commission for member countries to recycle 65% of all packaging waste and specifically 50% of all packaging plastic waste by 2025 seems more than relevant. The target for 2030 is 70% and 55%, respectively.

Given that such a large amount of packaging plastic is produced for consumption each year, some countries are performing rather poorly in relation to the set EU target. Even if the percentage of plastic packaging collected for recycling was an average of 41.8% in 2018 (Eurostat, 2020b), work needs to be done to reach the target. For instance, contrasting the recycling rate 26.9% of France to the 69.3% of Lithuania, there are great differences between the member states. Finland's recycling rate of 31.1% is quite far from the average.

For consumers in EU, packaging plastic constitutes around 61% of the 29.1 million tonnes of collected post-consumer plastic waste, and of this, 48% ended up in separate waste collection, and 52% in mixed waste (PlasticsEurope, 2019b). What is important to note is the actual amount of material in these fractions that ends up into the reprocessing phase: in the former case, 62% of plastic is reprocessed, 27% incinerated and 11% landfilled, whereas the percentages in the latter case are 6%, 57% and 37%, respectively. The alternatives to recycling or reuse may yield manifold issues ranging from the release of CO and CO_2 emissions and carcinogenic pollutants in incineration (Nagy & Kuti, 2016) to leaching of microplastics and harmful additives (e.g. plasticizers and heavy metals) in landfilling (Alabi, Ologbonjaye, Awosolu, & Alalade, 2019), although these two routes are heavily regulated on European scale, and are more relevant to other types of plastic waste.

What the EU constitutes as recycling is "any recovery operation by which waste materials are reprocessed into products, materials or substances whether for the original or other purposes", and "does not include energy recovery and the reprocessing into materials that are to be used as fuels or for backfilling operations" (Directive 2008/98/EC). This definition applies for packaging and more specifically packaging plastics as well. However, the calculation point of what constitutes as recycling for these materials has recently shifted: the previous directive on packaging and packaging waste (Directive 94/62/EC) took into account the amount of plastic coming into the plastic reprocessing plant, whereas the amended directive (Directive 2018/852), obliged to be followed as of 5 July 2020, weighs only what goes into recyclate production. As such, all the residues and rejects from treatment phase that currently fall under calculation will not do so in the future. According to estimates by PlasticsEurope (PlasticsEurope, 2019b), this change would have reduced the average recycling rate of 2018 from 41.8% to 29%. Thus, it is clear that there is an urgent need to both increase the efficacy of collected waste, whether it be in source-separated collection or mixed municipal solid waste (MSW), as well as finding new applications for recycled plastics and valorising rejects in all steps of the way.

This report outlines the work done in the Business Finland project PLASTin – ALL-IN for Plastics Recycling, in task 2.3. The purpose of the task is to provide a synthesis of needed pre-sorting technologies supporting EU's ambition to reach the set recycling goal of 55% of packaging plastics, focusing on the post-consumer segment. The report outlines the state of the art in plastic pre-sorting, treatment, separation and sorting, novel and future solutions for existing challenges thereof, as well as technical and business requirements for technology development and deployment.

Since there currently are no single repository for definitions for all relevant terminology, for the purpose of this report we define some terms below.

- Pre-sorting: partitioning of waste to different fractions after consumption by consumers or businesses. Most pre-sorting is done according to the material composition of the waste in varying degrees of subdivision (e.g. packaging, packaging plastic, PET bottles etc.), but also several different mixed waste fraction options exist.

- Collection: “the gathering of waste, including the preliminary sorting and preliminary storage of waste for the purposes of transport to a waste treatment facility” (Directive 2008/98/EC)

- Treatment: “recovery or disposal operations, including preparation prior to recovery or disposal”. This can also include “include preliminary operations prior to disposal including pre-processing such as, inter alia, sorting, crushing, compacting, pelletising, drying, shredding, conditioning or separating” (Directive 2008/98/EC)

- Separation: partitioning of waste based on the physical and mechanical attributes of the material. Includes ballistic, magnetic and sink-float separation.

- Sorting: partitioning of individual solid objects according to their material composition, regardless of size, in material or plastic recovery facilities. Here, varying subdivisions also play a role. Sorting may be manual or automatic. In this report, we focus on optical sorting technologies.

- Reprocessing: the generation of secondary raw material from waste. In the case of mechanical recycling, the material is usually granulates obtained from compounding waste plastic. In chemical recycling, the material can be feedstock, monomers or polymers, depending on the used method. The material generated through reprocessing has to fulfil End-of-Waste status as defined in (Directive 2008/98/EC) before it can be used in plastic production in European Union

- Plastic production: processing polymer material to manufacture a plastic product. The source of the material can be crude oil, waste plastic however treated or converted, or a combination of the two.

A relevant detail is that several intermediate storage phases exist between different steps of the recycling chain. This plays a role in the operational logistics as well as the output quality of the final reprocessed material.

Since this report is about packaging plastic, we focus on the most relevant polymer types therein. According to PlasticsEurope (PlasticsEurope, 2019a), polyethylene (LDPE, LLDPE, MDPE, HDPE), polypropylene (PP) and polyethylene terephthalate (PET) constitute the majority of the packaging plastic, with smaller amounts of polystyrene (PS, expanded polystyrene EPS) and polyvinyl chloride (PVC). These polymers do not solely exist as monomaterials in the waste stream, as there are many applications where multilayer materials are used. For example, multi-material flexible films for food packaging constitute approximately up to 20% of the total produced flexible film mass (Grant, Lugal, & Cordle, 2020).

2. Goal

The purpose of this report is to review the state-of-the-art in plastic sorting and their performance in each use case. Moreover, the existing bottlenecks and possible solutions to these challenges are considered. The goal of post-consumer plastic packaging sorting is to separate the incoming mixed plastic waste according to their polymer type as accurately as possible. The ultimate target is 100% homogeneous fractions of each polymer; in some cases, a mixed plastic fraction with defined polymer types may also be aimed at. In reality, 100% target is not feasible, as the sorting performance is imperfect and depends on many factors: the accuracy of identification, performance of the actuation, previous treatment steps as well as the material composition of the incoming waste.

For sorting facilities, four variables are most relevant for evaluating sorting performance of a sorting system: purity, yield, throughput and recovery. Purity is the amount of target material in the output relative to the total amount of the output. Yield is the amount of target material in the output relative to the amount of target material in the input. Throughput is total amount of output per time unit. Recovery is the total amount of output relative to the total amount of input. The amount in the definitions is usually characterised by mass or volume. To note is that purity is not a measure of the *cleanliness* of the output in terms of dirt, food residues or moisture, but rather in terms of presence of solid objects that are not the target.

As the 100% purity is not realised in practice, the Green Dot (*Der Grüne Punkt*) and *Deutsche Gesellschaft für Kreislaufwirtschaft und Rohstoffe mbH* in Germany have established realistic and realisable quality standards for sorting of plastic waste. The so-called DKR standards include for each polymer type (including all the commonly used packaging plastic for consumer use) as well as for mixed plastics the maximum amount of e.g. metal items, PVC, and other plastic particles that are allowed in the sorted stream that is output from the sorting facilities. For example, the strictest purity is established for PET bottles, in which under 2% of total mass can be residues (see Table 1). These standards are reflected throughout this report.

Table 1. Examples of DKR standards for sorted plastic wastes for recycling. Adapted from (IUT, 2019) and (Der Grüne Punkt).

Sorted plastic wastes	Metal items [w%]	Other plastic particles [w%]	Other residues* [w%]	DS** PE articles [w%]	Foamed plastics*** [w%]	Plastic foils [w%]	PVC [w%]	DS** PP [w%]	Min. purity [w%]
Plastic foils (mostly LDPE)	< 0.5	< 4	< 4	-	-	-	-	-	92%
Plastic hollow body (mostly HDPE)	< 0.5	< 3	< 3	-	-	-	-	-	94%
PP	< 0.5	-	< 3	< 1	< 0.5	< 2	-	-	96%
PET bottles (transparent)	< 0.5	< 2	< 2	-	-	-	< 0.1	-	98%
PE	< 0.5	-	< 3	-	< 0.5	< 5.0	-	< 3	94%

PS	< 0.5	< 4	< 2	-	< 1	-	-	-	94%
*Compostable waste (foods, garden rubbish)									
**Dimensionally stable									
***including EPS									

3. State-of-the-art in plastics sorting

As the treatment chain of the post-consumer packaging waste material is invariably tied to the utilized collection schemes, the available solutions are manifold and differ between the EU countries. The report outlines first the system in Finland, and then focuses on a number of examples from different European countries with different systems. The analysis of waste logistic and collection and how to optimize it is done in a different task, namely task 2.1.

3.1 Common technologies for separation and sorting

Around the world, certain technologies are commonly used in the separation and sorting of separately collected plastic waste or other collected plastic rich waste fractions. A brief review on each of them is given below.

3.1.1 Separation

Separation techniques, as explained previously, consists of partitioning input material based upon its physical and mechanical attributes. Commonly used technologies for plastic packaging waste separation are listed next.

3.1.1.1 Sieving or screening

Sieving is used for separating incoming solid material according to size, as determined by the design of the sieve. Commonly used screen types are the drum and disc screens. A drum screen is a large metallic cylinder with different size perforations around the surface that separate the material into different sizes whilst rotating. A disc screen consists of multiple solid parallel cylinders on top of which the waste material is input. Smaller size objects fall between the rotating cylinders while larger objects pass through. (Arina & Orupe, 2013)

3.1.1.2 Ballistic separation

Ballistic separation in essence separates 2D and 3D objects from one another. The separator consists of a long parallel plate screen deck that is inclined. Staggered mechanical vibration motion of the plates drive the light 2D material upward and heavier 3D objects downward. The separator may also include perforations in the decks to allow simultaneous sieving of fine particles. (Bilitewski, 2010)

3.1.1.3 Magnetic separation

Magnetic separation is used to get rid of ferrous metals, especially any material containing iron, such as steel. This can be done in various ways, but a simple approach is by applying a magnetic field on top of the conveyor belt carrying the waste material. Ferrous material is lifted and transferred to another stream while non-ferrous particles continue forward. (Gundupalli, Hait, & Thakur, 2017)

3.1.1.4 Eddy current separation

Eddy current is used for separating non-ferrous metals, such as aluminium and copper, from the stream. A rotating drum with a series of magnets with alternating polarity below a conveyor belt induce eddy electrical currents in conductive particles. The induced current results in the particles being repulsed from the drum, while non-induced particles remain in their trajectory. Moreover, ferrous particles are attracted towards the drum, allowing for separation into three fractions. (Amir, Karim, Mourad, & Amar, 2016)

3.1.1.5 Flotation

Flotation, also called sink-float separation, utilizes a liquid with known density (often water) to separate the waste material to fraction with greater and lesser density than the liquid. The method can be used to separate plastic flakes with differing densities from one another by submerging them in the liquid; one fraction sinks and the other floats. A difficulty in actualizing a very fine-grained separation is that many plastics, rather than having a single density, have a density distribution. However, for example PET, having a density greater than water, can be easily separated from common polyolefins (PE and PP) that have a density lower than water (Ragaert, Delva, & Geem, 2017).

3.1.2 Sorting techniques

Sorting units require a technology that probes the incoming material characteristics, often using a sensor. Sensor-based sorting usually utilizes the response of a material to transmitted electromagnetic radiation that is captured and analyzed. The response is dependent on the chemical composition of the material. Many different technologies exist, utilizing different spectrum of electromagnetic radiation. Commonly used techniques are listed next. The actual sorting units are reviewed in Section 3.7.

3.1.2.1 Near-infrared (NIR) spectroscopy

As the name suggests, NIR spectroscopy utilizes the near-infrared spectrum of optical radiation, namely the wavelength range 750 – 2500 nanometers (the exact wavelength range depends upon the definition). The sample is illuminated with suitable lighting, e.g. continuous spectrum halogen or wavelength-scanned laser, and the reflected (or transmitted) NIR spectrum is collected by e.g. an InGaAs sensor. The chemical bonds in the material absorb certain wavelengths of light by differing degrees and cause vibrations of the bonds, effectively modulating the spectrum of light scattered from the sample surface. This modulation is dependent on the bonds in the material, and as such enable distinguishing different materials. As plastic materials have many different carbon-hydrogen bonds, which readily absorb light in the NIR range, it is well suited for distinguishing different polymers from one another. (Scott, 1995)

In waste sorting facilities, in order to classify objects on a wide conveyor belt, line scanning is needed. Tomra utilizes a polygon mirror that rotates perpendicular to and above the belt. The polygon mirror reflects light from the source to the conveyor and due to rotation only illuminates a part of the belt surface at a time. Simultaneously, the scattered light is collected to the NIR sensor, effectively performing a line scan of the whole belt. (Van Dyk Recycling Solutions, 2020)

In addition to plastics, NIR has been demonstrated to be promising for discriminating between gypsum, , wood, foamed plastics, other plastics and bricks (Serranti, Palmieri, & Bonifazi, 2015) as well as different cellulosic materials such as cardboard, paper and pulp (Tatzer, Wolf, & Panner, 2005).

3.1.2.2 Ultraviolet (UV) and visible (VIS) spectroscopy

The operating principle of UV and VIS spectroscopy is similar to NIR, except the light utilized is in the ultraviolet (100 – 400 nm) and visible (400 – 700 nm) range. Sensors may use either or both (UV-VIS) of these ranges. In the VIS range, the colour of the sample is the most relevant feature for waste recycling, and with VIS spectroscopy it can be very accurately measured. UV-VIS can be used in applications where the phenomenon of fluorescence is of relevance. (Wu, et al., 2012)

A study from 2011 estimated that, using VIS spectroscopy sorter in the identification of clear PET bottles from a stream of clear, light blue and light green bottles, the method could reach purity and efficiency rates of 96.5% and 91.7%, respectively. Using an RGB-camera, the respective numbers were 86.5% and 77%, indicating a clear benefit in this case.

3.1.2.3 RGB camera

RGB cameras, i.e. photographic or linear CCD cameras, are used in applications where the visual features of the object are of relevance. The visual data is processed using computer vision algorithms that have been custom trained for a specific purpose. Computer vision for waste sorting is an emergent technology, and has been demonstrated to be usable in the laboratory for the detection of intricately different plastic granules (Peršak, Viltužnik, Hernavs, & Klančnik, 2020), for distinguishing several classes of waste (paper, cardboard, plastic, glass, metal and ”trash”) from each other (Ziouzios, Tsiktsiris, Baras, & Dasygenis, 2020), as well as by start-up companies for on-line waste sorting robots (Lukka, Tossavainen, Kujala, & Raiko, 2014). Some commercial solutions are available utilizing RGB cameras, such as REDWAVE C and UniSort C that can be used to sort plastic by colour. (4R Sustainability Inc., 2011)

As mentioned, RGB cameras coupled with machine learning have been demonstrated to be usable highly efficient in distinguishing different coloured granulates from each other, with an average accuracy of 90.5% using 9 classes with 150 distinct samples per class (Peršak, Viltužnik, Hernavs, & Klančnik, 2020). Similar study showed that training an AI model using photographs of paper, plastic, glass, cardboard, metal and trash could reach an average accuracy of 96.57% (Ziouzios, Tsiktsiris, Baras, & Dasygenis, 2020).

Studies have also been made to see whether adjacent and overlapping objects in an RGB camera image could be segmented using image analysis (Wang, Peng, Huang, & Sun, 2019). It was found that the image analysis algorithms worked only on adjacent objects, i.e. objects in contact but not overlapping. Moreover, it was demonstrated that RGB camera - based colour classification of PET bottles could reach accuracies of 94.7% with 1446 bottles and 7 different colours.

3.1.2.4 Hyperspectral imaging (HSI)

Hyperspectral imaging extends the principles of spectroscopy to include spatial dimension(s). In essence, it can be viewed as a combination of an RGB camera and a spectroscope; instead of collecting three colours, it collects a wide spectrum for each pixel. HSI can be done in a variety of different wavelengths, much like spectroscopy. For plastic recycling, NIR HSI is of most relevance. Hyperspectral cameras usually operate as line scanners in a push-broom mode: the camera constitutes of multiple parallel NIR spectroscopes, which can simultaneously scan points in a line. An actuator, for example a conveyor belt moving the material under the scanner, then generates the third dimension, resulting in a 2D image with each pixel having a spectral dimension as well. HSI requires a light source much like spectroscopy, and in the NIR range a halogen light or broad-spectrum LEDs are suitable. (Karaca, Ertürk, Güllü, Elmas, & Ertürk, 2013) HSI is a very novel solution that has seen some usage in recycling facilities.

3.1.2.5 X-ray fluorescence spectroscopy (XRF)

X-ray fluorescence is a phenomenon in which atoms of a material, when coming in contact with X-rays, are ionized, i.e. its electrons displaced from its ground energy state to a higher energy (excited) state. Another electron may replace the vacancy in the ground state from a higher energy state, which results in secondary X-rays being emitted; further, the now-vacant higher energy state may be filled by one above that, resulting in a cascade of X-ray emissions. As these emissions are quantized, and the energy levels of different atoms vary, they can be used to accurately determine the atoms the material consists of. Thus, bombarding material with X-rays generated in an X-ray tube and gathering the scattered spectrum to e.g. a CMOS detector, the intensity peaks corresponding to different elements can be distinguished (Jenkins, 1999).

As X-rays have a very high energy, they can be used to distinguish elements with high atomic weight, such as chromium, lead and copper. It is also suitable for distinguishing bromine, which is an element in brominated flame retardants, often used in e.g. WEEE plastics (Guzzonato, Puype, & Harrad, 2016). Moreover, it can also be used to screen for PVC in waste material, as it can detect the chlorine present in the polymer (Turner & Solman, 2016).

XRF has been reviewed to be capable of distinguishing elemental bromine and chlorine in concentrations as low as 100 - 200 ppm (Beccagutti, et al., 2016). A comprehensive study evaluated a handheld XRF device, Niton XL 2 by Thermo Scientific, and found that the limit of detection for bromine in WEEE plastics for this device was 300 ppm (Aldrian, Ledersteger, & Pomberger, 2015).

3.2 Recycling in Finland - overview

According to Eurostat, 135 kilotonnes of waste plastic packaging was generated in Finland during 2018 (Eurostat, 2020a). As mentioned in section 1, the collection rate of Finland in that year was 31.1%. Thus, approximately 42 kilotonnes of waste was collected. As Finland has established a landfill ban for plastics, the remainder was utilized in energy recovery along with the rejects.

In Finland, municipalities are obliged by law to organize the management of municipal solid waste (MSW) (Waste Act 646/2011, Section 32). The extended producer responsibility applies to most consumer plastic packaging (i.e. plastic packaging that surrounds consumer packaged goods) and post-consumer plastic packaging waste. Consumer packaging means the packaging of goods that a consumer consumes. The pre-sorting fractions in households and housing companies are varied; the waste can be sorted according to their material composition to biowaste, paper, glass, metal, cardboard and mixed MSW. Beginning from 2016, in many cases also the separate collection of plastic packaging is provided.

It is expected that the national Waste Act reform will oblige municipalities to provide housing companies with more than four housing units in urban areas bins for collecting plastic packaging (Kauppila, 2020). This has previously been obligatory only for housing companies with over 20 housing units. At the moment, source-separated collection for packaging plastic is managed by Suomen Uusiomuovi, with the contract service provider Rinki that has over 600 bring points around the country (Rinki, 2021). Suomen Uusiomuovi also maintains the transportation terminals to which the collected plastic packaging waste is transported and is responsible for the recycling of the collected volume.

Additionally, a deposit system for beverage containers made from glass, aluminium and PET is in place. Consumers bring the containers to reverse vending machines in stores after consumption to get remuneration. In 2018, it was estimated that 90% of all the sold PET bottles were recovered with the deposit system. This amounted to 13.9 kt of PET (Palpa, 2019), of which half was reprocessed in Finland and half shipped abroad (Helsingin Sanomat, 2018). To note is that the retail company Lidl has their own deposit system for PET bottles sold in their stores.

There is currently only one industrial-scale reprocessing facility for separately collected post-consumer plastic packaging in Finland, namely the plastic refinery in Riihimäki by Fortum Waste Solutions. This facility, contracted by Suomen Uusiomuovi, handles most of the waste fraction; a segment of this is shipped abroad for reprocessing (in 2020, 33% was transported abroad). In 2018, approximately 11.4 kilotonnes of plastic packaging were brought to the facility. In 2019, the number had grown to 20.4 kilotonnes. (Uusiouutiset, 2020) The amounts of plastic packaging generated and brought to Fortum by the business sector were 14.8 kt in 2018 and 19.7 kt in 2019. According to YLE in 2019, the reprocessing rate of this material was reported to be around 75% by Fortum; the rest was utilized as recovered fuel (YLE, 2019). However, according to a very recent news article, in the last few years the reprocessing rate has actually been half of that, 37%, (YLE, 2021). The main reason for this, according to Fortum, is that there is not enough market demand for the increased amount of mixed packaging that are reprocessed. (Fortum, 2021)

When it comes to the mixed MSW from post-consumers, according to studies from 2016 (Liikanen, et al., 2019) and 2018 (Dahlbo, Poliakova, Mylläri, Sahimaa, & Anderson, 2018), plastic may represent around 15% of its total mass. By studying mixed MSW waste from post-consumers in Uusimaa and Southwest of Finland, it was found that 6.8% was hard and 7.6% was soft packaging plastic by mass (Dahlbo, Poliakova, Mylläri, Sahimaa, & Anderson, 2018). Moreover, in an experiment performed in 2015, out of a sample of 130 kg of plastics recovered from mixed MSW, up to 87.3% would have been recyclable (Poliakova, 2018).

According to Statistics Finland, in 2018 Finnish municipalities produced 1.5 megatonnes of mixed MSW, of which material 12.7 kt were reprocessed and reused (Suomen virallinen tilasto, 2018). It is not defined how much of this material is plastic, but what is clear is that massive amounts of material, including plastic is incinerated each year.

Calculating the collected amounts of waste from each of these known streams in 2018, i.e. PET bottles and separately collected packaging plastics from consumers and businesses, we get 40.1 kt, a number very close to one reported by Eurostat (42 kt). It can be assumed that the rest, 1.9 kt, was plastics recovered from the mixed MSW fraction.

3.3 Treatment, separation and sorting in materials recovery facilities in Finland

In this section, the three identified tracks for post-consumer plastic collection are looked into from the viewpoint of sorting.

3.3.1 Closed loop - PET bottles

Pet bottles collected with reverse vending machines are baled and sent to the single reprocessing facility in Finland, Pramia Plastic (Salminen, Turunen, & Fjäder, 2020). The sorting process (Pramia Oy, 2020) is as follows. The bottle label sleeves are removed and sent to energy recovery as briquettes. Two optical sorters sort the bottles to clear and coloured PET. Manual quality assurance is used in the case of clear PET bottle stream. Metals and aluminium are removed from the stream after shredding. The material is washed, cleansed and dried several times. Density-based (sink-float) separation fractionates the material of the bottle (PET) from the bottle cap (PP and HDPE). Further colour separation is done to the clear PET flakes to remove possible coloured particles as well as aluminium. The final sorted fractions are coloured PET, clear PET and mixed-colour bottle caps (around 50% HDPE and 50% PP) (Fråne, et al., 2014). What is significant is that Pramia is able to provide food contact approved granulates from some of the waste PET, and also to reprocess them into clear bottle preforms for new beverage container manufacturing (Suomen Uusiomuovi Oy, n.d.).

The colour sorters used are the SPEKTRUM range sorters by Sesotec (formerly known as S+S Separation and Sorting Technology GmbH), suitable for glass and plastic sorting (Sesotec). The range utilizes high performance colour or monochrome CCD cameras, with higher end sorters also having metal detection and NIR spectroscopy as an option (Sesotec). The sorters can output the material into two streams.

3.3.2 Separately collected plastics

In the Fortum refinery, the plastic packaging waste material undergoes several steps of sorting and treatment (Fortum Waste Solutions Oy, 2020). Ballistic separation is used for separating 2D and 3D materials (namely, film from rigid plastic); rotating drum sieve for separating objects by size; NIR sorting for fractionating into polymer types; and metal detection for separating magnetic and non-magnetic metals from plastics after shredding. Polymer sorting is accomplished using 11 NIR sorters (apparently all) by REDWAVE (Uusiouutiset, 2016) that fractionate the material to LDPE, HDPE, PP, PET and plastic mix (Fortum Recycling and Waste Solutions, 2018). LDPE, HDPE and PP are reprocessed in-house.

REDWAVE has a range of sorters for many applications, such as plastics sorting, electronic waste and waste glass processing. For plastic sorting, the REDWAVE 2i is the most optimal. It combines NIR sensors, inductive metal detector and high-resolution RGB cameras in order to sort e.g. MSW, paper, glass, and plastics (REDWAVE (a), n.d.). The polymers it can recognize are different colours of PET, HDPE + LDPE, PP/PS and PVC. The sorter can output two or three different streams. REDWAVE also has sensor technologies for X-ray fluorescence spectrometry, which can be used for detecting brominated flame retardants in WEEE streams, as well as hyperspectral imaging (REDWAVE (b), n.d.). The company uses machine learning and AI for classification of detected objects.

In a report from 2019, the material composition of a single 11 kilogram batch from the reject fraction from this facility was studied and quantified according to DKR standards (Briedis & Syversen, 2019). The results are shown in Figure 1; as can be seen, the batch consisted of mostly category other waste/residues, which apparently includes “glass, liquid packaging boards, aluminised plastic, rubber, wood, nappies, food, garden waste, stones”. However, the 11 kilogram sample is very small, and cannot be generalized as universal reject output; a more in-depth study should be conducted, as there are little studies available in this domain.

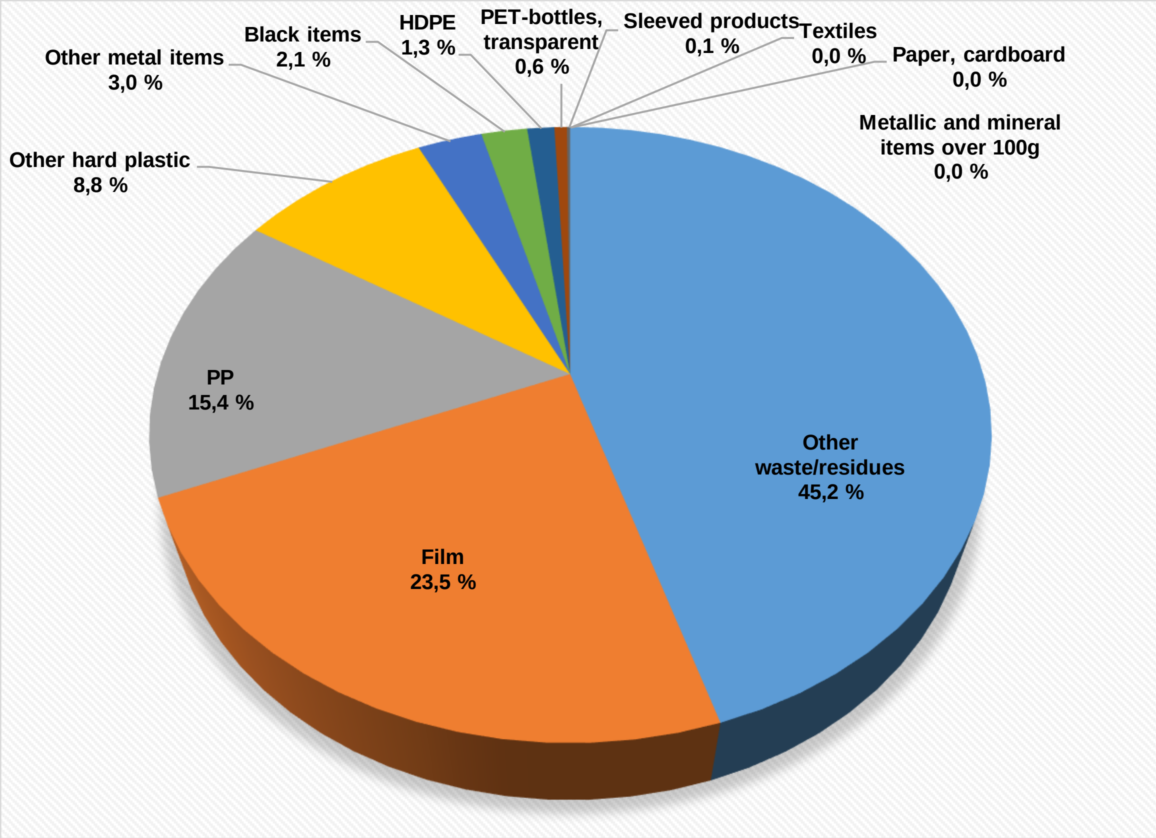

Figure 1. Material composition of a single 11-kilogram batch from the reject fraction of the Fortum plastic refinery.

3.3.3 Mixed municipal solid waste (MSW) and waste-to-energy

In 2016, Finland only had two materials recovery facilities for managing mixed waste, namely Fortum's Eco Refinery (Fortum, 2020) and Päijät-Hämeen Jätehuolto's mechanical sorting facility LATE (Laaksonen, Merilehto, Pietarinen, & Salmenperä, 2017). These facilities handle post- consumer waste-to-energy fraction as well as wastes from businesses and industry (Kauppalehti, 2016; STT, 2016) and are currently in operation. Recently, a third such facility was built in Oulu by Oulun Energia: however, the Rusko waste sorting facility does not sort mixed MSW from consumers (Oulun Energia Oy, 2021); the recovered plastic material, along with e.g. cardboard and wood, is used as refuse-derived fuel (RDF).

Both facilities, the Eco Refinery and LATE, sort plastic material and previously also transported it to the Fortum plastic refinery for reprocessing. However, according to Fortum, this is not the case as of present; the MSW fraction brought to the Eco Refinery generally consisted of very little plastic (approximately 3 - 4 %) and a lot of biowaste, which contaminated the batches such that only hard plastics could be reprocessed. The amounts were not large enough for economically feasible operation, and reprocessing of this material was discontinued.

For the case of LATE, Fortum ran some tests with their output plastic fraction, but the sorting was deemed incomplete, as different plastics were mixed together. Due to huge growth in the collection of source-separated plastics, Fortum could not find capacity to further sort the material from LATE, and the input from this facility was discontinued.

The Eco Refinery managed 100 kt of mixed MSW, of which 4 kt was estimated to be separable plastics in 2017 (Fortum, 2017). The LATE facility managed around 66 kt of waste (Laaksonen, Merilehto, Pietarinen, & Salmenperä, 2017), of which 1.5 kt was plastic in 2019 (Salpakierto Oy, 2019). Assuming that these numbers were similar in 2018, the calculated recycled fraction of 1.9 kt would indicate that around 66% of the sorted plastic was incinerated.

The facilities follow roughly the same set of sorting and separation steps. Following the procedure of the LATE facility (Ramboll, 2020), the incoming waste-to-energy material is first crushed, and ran through a rotary drum sieve, after which the larger objects undergo ballistic separation. Magnetic metals and aluminium are removed. Wind sorter is used to separate heavy material, such as glass, concrete and ceramics from the stream. An optical sorter is used for sorting the remaining light material into different fractions, most likely plastics and non-plastics.

The used optical sorters are Mistral Dual Vision by Pellenc ST. According to Pellenc (Pellenc ST), it can sort hard plastics, plastic films, fibers, wood and organic material, and account for colour. It utilizes a single scanner for both NIR and VIS spectroscopy. Apparently, it can output the material up to three different streams, and is able to recognize different colours of PET, HDPE and PP, as well as PVC, PS and plastic film (Innovations Report, 2012).

3.4 Examples from other countries

3.4.1 Belgium

In Belgium, a separate kerbside collection scheme is established for plastic packaging, metal packaging and drink cartons, so-called PMD collection; more recently, this scheme was extended to all packaging instead of only hard packaging. The sorting process for this fraction by the company Indaver, apparently in the community recycling centre in Willebroek (Indaver), is rather similar to the mixed MSW outlined in Section 3.3.3. Some differences are that after magnetic and non-ferrous separation, drink cartons are separated via optical sorters. Furthermore, ballistic separation is done only for the mixed plastic fraction. Shredding is not done in any phase. The plastic fraction is sorted by 5 optical separators into PE, 3 colours of PET and PP. (Ragaert, Delva, & Geem, 2017) The facility treats 60 kt of PMD waste annually.

Belgium also manages some source separated mixed plastic packaging waste from the Netherlands and Germany. An SME company Eco-oh! manages some of this material. As the collection scheme accepts all plastics, many contaminants for the most reprocessable materials, namely HDPE, PET and PE, exist. The utilized treatment includes a coarse shredder, a rotating drum washer, friction washers, fine shredder and float-sink separation. The sink fraction is collected, and the float fraction (made of PP and PE) is further separated using a wind shifter that separates the material into hard and soft mixed polyolefin fractions, i.e. HDPE + PP, and LDPE + some PP, respectively. (Ragaert, Delva, & Geem, 2017)

3.4.2 Austria

According to a report from the EU project PlasticZero, in the Graz region in Austria, waste contractor Saubermacher has a central sorting facility for packaging waste (Plastic ZERO, 2014). The plant outputs sorted paper, cardboard, plastics and RDF. In 2013, only *certified* packaging was sorted; Austria had implemented a take back program that mandates "all manufacturers, distributors and importers that place packaging or packaged goods on the Austrian market to take these packaging materials back free of charge and ensure their recovery or reuse". (Municipal Waste Europe, 2015) Alternatively, they may "participate in a collection and recycling system subject to a licence fee". (Reclay Group, n.d.)

One of the collection schemes for most households in Austria, including the Graz region, is the so-called "yellow bag" scheme, in which all packaging made of plastic, composite, wood, textiles or ceramics are commingled (Plastic ZERO, 2012). This is the fraction that Saubermacher handles. In 2013, the facility reported to have high quality requirements for the output: HDPE bottles and LDPE film have a minimum purity of 95%, and white, light blue and green PET bottles the percentage is 98%; the output purity requirements in Austria in 2013 were 96 – 99% depending on the polymer. The treatment process involves a drum screen, magnetic separation, air classifier, ballistic separator, NIR sorter and manual quality control before baling. In 2018, the facility was updated, and now also sorts aluminium cans and beverage cartons. Novel REDWAVE sorters are used in the plant. The facility can sort 32 kt of material annually. (Recovery, 2018)

3.4.3 Sweden

Recently in Motala, Sweden, a fully automated plastic sorting facility was opened. It sorts source separated plastic packaging with 22 NIR sorters, capable of sorting the material into PE film, PET bottles, PET trays, white/transparent HDPE, mixed colour HDPE, PP, mixed plastics, and metals. (TOMRA Sorting Solutions, 2019) Before NIR sorting, the material is separated using magnets, drum screen, wind shifting and air ballistics. The facility can sort 120 kt of material annually. The reject of the sorting process is approximately 45% of the input. This reject consists mainly of non-recyclable packaging, non-packaging plastic, moisture and non-plastics. (Larsson, 2018) Non-recyclable in this context means black plastics and polymers that cannot be profited from as recycled material.

3.5 NIR spectroscopy – review

3.5.1 Accuracy

Evaluating the NIR sorting units' accuracies in the plastic or material sorting facilities is not a trivial task. The waste fraction undergoes many different separation phases before reaching the sorter unit that is calibrated to deal with a plastic-related sorting task. As a result, the sorter, not calibrated for e.g. residual metals or paper, may not work as expected, leading to lower purities not due to the NIR sorter itself, but rather due to the imperfections in the previous sorting phases.

Nonetheless, the accuracies of NIR sorters have been evaluated in MRFs and PRFs in the UK and mainland Europe a decade ago (Axion Consulting, 2010). Example MRFs demonstrated product purities in 3 different cases, and in PRFs two cases were evaluated. The lowest purity was established for PET, with purities of 65%, 73% and 88% in the cases. For HDPE and PP, the purities were around 90%. The purities of the fractions were improved with post-NIR manual sorting.

In PRFs, a finer sorting was done also according to colour for PET and HDPE. However, since NIR does not operate in the visible spectrum, this kind of characterization is not robust and can only detect proxy effects (e.g. higher or lower reflectivity in the NIR spectrum), not the actual visual colour. Nonetheless, the classification to coloured / non-coloured plastic was rather poor for the coloured PET; in this fraction, 53% of the material was coloured PET, 40% clear PET, with the remainder material being other polymers (total polymer purity 93%). In the other example case, with coloured PET class, the percentages were 33% coloured PET and 62% clear PET (total polymer purity 95%). As such, the colour sorting efficiency is very poor. Utilizing VIS-range spectroscopes would clearly benefit these facilities. In general, the report outlines that typical NIR sorter system accuracy is in the range 80 – 95%, while well-adjusted systems can reach purities of over 95%.

A more recent study looked at the output fraction purities of materials recovery facilities in two countries, Norway and Finland (Briedis & Syversen, 2019). The facility in Norway, by Romerike Avfallsforedling IKS (RoAF), is a fully automatic sorting facility that handles organic waste, metals, plastics, paper and cardboard (ROAF, 2015). Plastic sorting is done using 13 optical sorting units, VIS and NIR (TOMRA, 2016). The facility in Finland is the aforementioned Fortum plastic refinery, using 11 NIR sorters.

The tested fractions and purity calculations were generated according to DKR standards. The findings of the study are shown in Table 2. The findings between the two facilities, however, are not directly comparable due to lower amount of collected material for testing. Moreover, in the RoAF facility, two different batches were collected, and their weighted average was used in the final result. The two facilities are also running with different capacities; Fortum is currently running on rather full throughput (around 30 kt per year), while RoAF has a throughput capacity of over 30 tons per hour but sorted only a total of 40 kilotons in 2016 (Eule, n.d.). Nonetheless, these numbers give some indication about the performance of modern NIR sorters.

Table 2. Output fraction purities of the two facilities and the collected test amount.

	ROAF		**Fortum**	
Fraction	**Collected amount [kg]**	**Purity [%]**	**Collected amount [kg]**	**Purity [%]**
PP	61.0	96.8	15.13	87.3
HDPE	77.6	91.5	14.21	87.2
LDPE	40.0	95.6	6.49	86.9
Mixed plastics	92.2	62.4	27.05	80.2

Another study conducted in 2011 compared automatic optical sorting systems for recycling plastic containers by different manufacturers (4R Sustainability Inc., 2011). In the report, the accuracies of the devices were also listed in some specific use cases, apparently defined by the companies themselves. Nonetheless, it outlined 27 different units for sorting whole plastic containers and 27 units for sorting shredded plastic flakes. The sorters' primary application and what plastics it sorts, as well as the throughput were listed.

For the 20 listed whole container sorters using NIR, the reported accuracies were very high, with most units reported as being capable of achieving up to 99% sorting accuracy. The sorters are listed according to whether they operate on commingled, contaminated single-resin or mixed plastic streams. Colour sorters also reach very high accuracies, and the X-ray based VinylCycle can reach 99% accuracy in sorting out PVC from PET. , Less NIR units seem to be available for plastic flake sorters, as only 8 were listed. Nonetheless, the reported accuracies range from 80% to 99%. Colour sorting via RGB or linear CCD cameras reportedly reach accuracies of over 95%, and XRF-based methods can sort plastics containing brominated flame retardants (BFR) with up to 99% accuracies.

Unfortunately, the manufacturing companies rarely share the technical specification of their sensor units openly. As such, the effect of the NIR wavelength range used were not evaluated. However, in a study conducted in 2018 (Yan & Siesler, 2018), four different hand-held NIR spectroscopes were evaluated based on their performance to distinguish different plastics, namely PE, PET, PP, PS and PVC. The wavelength ranges of these devices were very different; the narrowest range was 1550 – 1950 nm, and the widest 1298 – 2606 nm. As expected, the best results were obtained with the latter, and the poorest with the former. The type of detector also has an effect; the two other spectrometers had a similar range to each other (908 – 1676 nm and 900 – 1701 nm), but the Viavi MicroNIR has an array detector, whilst the DLP NIRscan has a grating and a single-element detector. The single-element detector could distinguish the polymers much better.

3.5.2 Limitations of NIR

Several problems are associated with using NIR spectroscopy that hinder its all-around performance. These include black and dark plastics: colorants may absorb all the radiation, giving no reflective signal; multilayer films: conventional NIR sorters identify the material according to which side of the film happens to align with the detector; incorrect prediction due to e.g. sleeves, dirt and overlapping objects (Ragaert, Delva, & Geem, 2017). Moreover, there is no feasible way to distinguish between food grade and non-food grade packaging. Given that novel bio-based plastics and biocomposites gain traction, NIR or some other technique has to be demonstrated to work for these materials as well.

The results on the discrimination between HDPE and LDPE with NIR HSI or spectroscopy have been conflicting. Using a multiclass PLS-DA based algorithm for classifying different plastic pieces, namely PP, PS, HDPE and LDPE, one study found that HDPE and LDPE were indistinguishable (Vidal, Gowen, & Amigo, 2012). Using a hierarchical classifier, i.e. multiple cascaded PLS-DA algorithms, another study found that LDPE and HDPE can indeed be distinguished, even if their spectra are very similar (Bonifazi, Capobianco, & Serranti, 2018). However, only single-coloured samples were considered, and the effect of colorants may have an effect on the classification accuracy. On-line validation is needed.

3.5.3 Penetration depth of optical radiation

Several studies have been conducted to determine the penetrability of light into polymers. A very early study conducted quantified the so-called wavelength-dependent information depth of 60-% crystalline LDPE (Haanstra, et al., 1998). The information depth is defined as the thickness of the sample with which 50% of the radiation is lost in terms of intensity reaching the sensor. Two modes of measurements were considered in the VIS and NIR range: reflectance and transmittance, using apparently a continuous-spectrum light source. In the transmittance mode, the information depth ranged from 100 - 830 micrometers. In the reflectance mode, which is more relevant to NIR plastic sorting, the depth ranged from 0 mm to 2.5 mm; in the most strong absorption band at 1730 nm, no radiation is reflected, while for most of the VIS-NIR spectrum the depth was over 0.5 mm.

The study above did not consider how a spectrum of a sample below a polymer film would show in either mode. A more recent study has looked into reconstructing the reflectance spectrum of a sample below different thicknesses of PE film (Pomerantsev, Rodionova, & Skvortsov, Diffuse Reflectance Spectroscopy of Hidden Objects. Part II: Recovery of a Target Spectrum, 2017a). Basing on their previously developed phenomenological approach (Pomerantsev, Rodionova, & Skvortsov, 2017b) it was determined that the signal could be quite accurately reconstructed up to 0.7 mm PE layer thickness. The study looked into the

NIR spectrum in the range 1100 - 2500 nm, and, as they utilized diffuse reflectance spectroscopy, most probably a continuous light source was used.

Other studies have considered the wavelength-dependent transmittance of different polymers with constant thicknesses in the VIS-NIR range (Wang, Chang, & Hsu, 2018). In these cases, PP, PC and PMMA with 2 mm thicknesses were considered in pure form as well as doped with additives. Strong absorption bands notwithstanding, the transmittance of pure plastics were over 50% in most wavebands in the NIR range. In the VIS range, the transmission of all pure plastics was over 90%.

In the case of laser radiation, a similar study has been conducted (Genna, Leone, & Tagliaferri, 2017). In the study, the signal characteristics of a 975 nm laser beam through a 3-mm thick HDPE plate was investigated. It was found that the loss of laser power was as follows: 8.7% directly reflected at the surface, 48.6% transmitted through, 39% scattered and 2.4% absorbed. Compared to (assumedly) halogen light source (Haanstra, et al., 1998), where the transmittance of about 0.45 mm thick HDPE plate is around 50%, the benefits of laser radiation is clearly seen.

What needs to be considered is that even though the penetration depth could be in the millimeter range, actual detection based on the spectrum is not as clear cut. As such, for example in identifying multi-layer films, the reflected signal from the layers beyond the surface polymer needs to be strong enough to reach the detector when measuring in the reflectance mode. In the next section, research into multi-layer material recognition is considered as well.

3.6 Novel solutions

Some novel solutions that have been demonstrated to be applicable to the sorting of plastics are enumerated next. Most of them have seen use in actual sorting units, while some are as of yet only have been demonstrated in the lab scale.

3.6.1 NIR hyperspectral imaging

Hyperspectral imaging (HSI), is a natural extension to NIR spectroscopy that allows for both the usage of computer vision as well as spectroscopy-based classification algorithms. The benefit of fusing these two is illustrated in Figure 2. Instead of identifying, on the PRF conveyor belt, single measurement pixels like the regular NIR spectroscope, an image is also gathered. From this image, it can be deduced if the object is made of multiple materials, for example, a PET bottle with a cap made of PE. Furthermore, if the bottle were surrounded with a label sleeve, the computer vision algorithm could be trained to disregard the sleeve material and only take into account the underlying bottle material, for example based on the total area of the object.

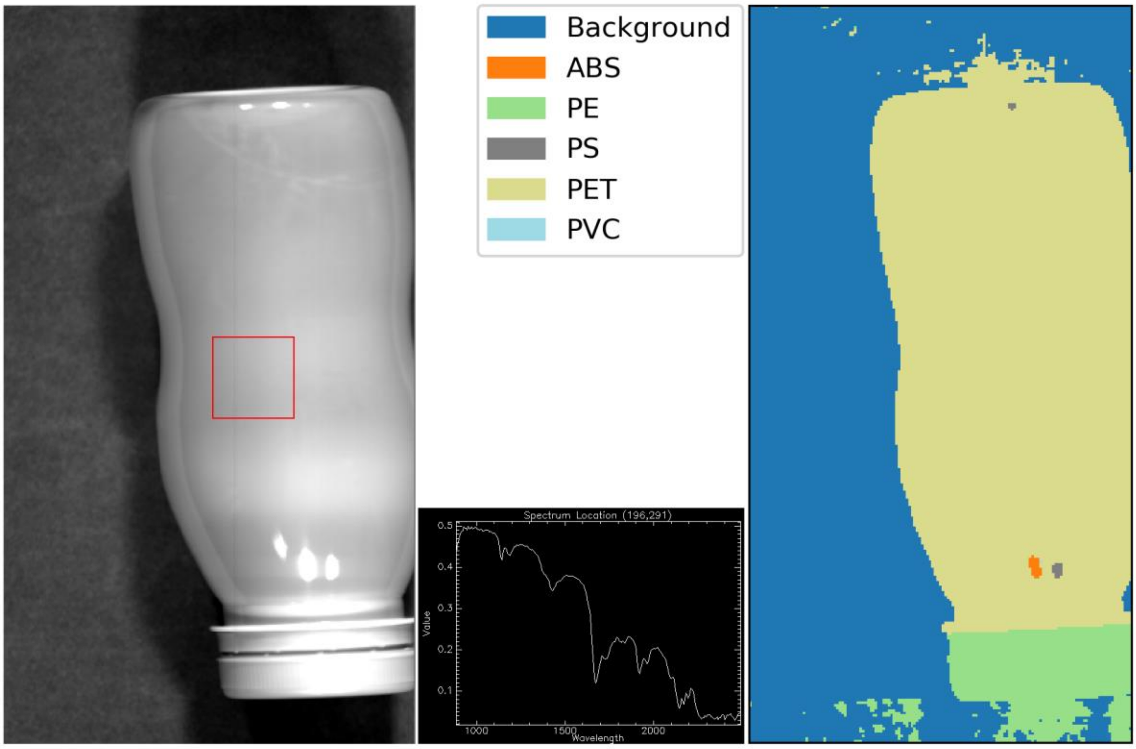

Figure 2. Example of hyperspectral image classification. On the left, a false-colour greyscale image is shown of the object that was imaged with Specim SWIR (1000 - 2500 nm) hyperspectral camera. The spectrum of the area marked with red square is shown on the graph at the bottom. On the right, the pixel-wise classification results based on the spectra are displayed, with the colour representations given in the legend on the top of the image. As can be seen, the bottle is correctly deduced to be made of PET with a PE bottle cap. Image courtesy of VTT.

When it comes to detecting multimaterial objects, HSI has been demonstrated in laboratory conditions to be able to distinguish biocomposite materials from plastics and biomaterials (Sormunen, et al., 2019). Moreover, the NIR spectrum of the bio-based polymer PLA can be used in distinguishing it from 8 other plastics.

In another study, the classification of multilayer films made of LDPE and PP based on NIR-HSI was studied (Chen X. , Kroell, Feil, & & Pretz, 2020). The results were promising; the spectrum analysis –based algorithm could classify most pixels correctly as belonging to either LDPE, PP, or as PP+LDPE. Building on the results, more samples with several layers were studied, and the pixel-wise classification accuracy was, on average, 96.3% and 80% for two- and three-layer transparent samples, respectively (Chen, Kroell, Wickel, & Feil, 2021). Opaque samples were studied as well: for these, the accuracies were quite similar except for black coloured patches. Using a highly reflective background increased the accuracy of transparent samples by about 6%. However, a drawback in these two studies is that the training and test pixels in the hyperspectral images came from the same plastic samples; the models should be further validated with an external sample set.

Some companies manufacture units that utilize HSI instead of the conventional NIR sensor. For example, the STEINERT Unisort PR utilizes a line scanning hyperspectral camera, allowing for both spectral and spatial data processing. The unit also contains a high-resolution RGB camera, allowing for efficient computer vision algorithms for object recognition (STEINERT).

3.6.2 Laser-induced breakdown (or plasma) spectroscopy (LIBS / LIPS)

LIBS is a rather novel technique in the study of plastics, but recently there has been a huge increase in the number of related publications (Liu, et al., 2019), especially in the WEEE domain (Costa, et al., 2018). In LIBS, a highly energetic laser is focused on sample surface; the material of the illuminated point forms a plasma, and the atoms are excited. As the excitation state is relaxed, the excited ions and electrons return to ground state, releasing photons whose energy are characteristic to each atom and ion. These photons are captured via a detector and a spectrum is formed, from which each individual element can in theory be deduced. An advantage of LIBS is that it is not simply a surface probe; as it generates plasma, it also ablates the material, allowing for seeing the spectra of material beyond the surface.

The operation of LIBS is quite similar to XRF. However, as XRF can only distinguish heavier atoms, LIBS can analyze much lighter elements in addition to the heavy ones. For example, LIBS has been demonstrated to be able to distinguish PET, PE, PP and PS from each other with an average class accuracy of 91.5% using 30 different plastic samples per class (Unnikrishnan, 2013). In another study, accuracies of 91 - 100% was reached for identifying ABS & PS, PE, PC, PP and PA classes (Costa, Aquino, Paranhos, & Pereira-Filho, 2017). LIBS has also been demonstrated to distinguish dark PVC samples on-line by the means of detecting the chlorine peak, correlating very well with the XRF validation measurements (Huber, et al., 2014). It shows potential to discriminate between LDPE and HDPE (Costa & Pereira, 2020).

LIBS has also been used in the domain of WEEE sorting, with distinguishing e.g. different BFRs and more significantly samples with different concentration of the same BFR from each other, with an average accuracy of 100% using principal component analysis and linear discriminant analysis (Stefas, Gyftokostas, Bellou, & Couris, 2019); however, the number of samples in the test set was rather low, 72 samples in 12 classes. Thus, more data is needed to validate the results.

The Stena Recycling facility in Sweden is the first facility in the world that utilizes LIBS in a waste sorting line; they use it for high-speed detection of aluminium (Stena Recycling, n.d.). A few companies exist that offer LIBS devices for on-line sorting use, for example Bertin Instruments (Bertin Instruments, n.d.), SECOPTA (SECOPTA analytics GmbH, n.d.) and STEINERT (Recycling Product News, 2018).

3.6.3 Raman spectroscopy

Raman spectroscopy is a method similar to NIR, but instead of a continuous spectrum light source, it utilizes a high-intensity laser on a single wavelength. As the sample is illuminated, some light is inelastically scattered, resulting in the scattered photons having a lower energy than the incoming laser. This shift in energy, called the Stokes shift, is dependent on the molecular structure, and shifts occur in varying degrees, producing a spectrum that when collected is characteristic of each molecule. Similar to NIR, Raman is a surface probe, and is hindered with the same challenges.

Saimu Corporation in Japan has a demonstration facility that utilizes Raman in on-line measurements. They have demonstrated to be able to distinguish between different polymers in shredded form, and have shown promise in detecting flame retardants inside the polymer matrix as well as identifying black plastics (Kawazumi, Tsuchida, Yoshida, & Tsuchida, 2014). The reached sorting purity in the facility is 95%, with a recovery rate of 80% (Saimu Corporation, n.d.). Saimu Corporation seems to be the only company that has developed an exclusively Raman based sorter for industrial use.

Unisensor also has their own sorting units, Powersort 200 and Powersort 360, that utilize Raman in tandem with absorption and fluorescence spectroscopy in UV-VIS-NIR range (Unisensor, 2017). In the study outlined in section 3.5.2, the Unisensor Powersort 200 was also reviewed (4R Sustainability Inc., 2011). The reported accuracy was 98% or higher, and the unit can be used for sorting flakes of all polymers. Moreover, it can be used to distinguish certain additives, e.g. titanium dioxide inside PET matrix (Unisensor, 2017), as well as able to identify some carbon-black plastics (PET and PS but not PP) in the flake form (WRAP, 2011).

Raman spectroscopy has been demonstrated to be able to distinguish HDPE-LDPE blend concentrations in the laboratory (Silva & Wiebeck, 2019). Moreover, it has been used to study a case similar to multilayer material identification. In the study (Nicolson, et al., 2017), the maximum thicknesses of transparent PET and opaque PP layers covering a sample of liquid ethanol such that the ethanol could still be determined from the spectrum were investigated. It was found that using conventional Raman with excitation wavelength 785 nm, the maximum thicknesses were 9 mm and 2 mm, respectively. Using spatially offset Raman, the maximum thicknesses increased to 21 mm and 9 mm.

3.6.4 Mid-wavelength infrared (MIR) spectroscopy and MIR HSI

MIR spectroscopy operates on the same principles as NIR, but with higher wavelengths, namely in the range 3000 – 8000 nm. Recently, many different studies have been conducted on the applicability of MIR spectroscopy in identifying different black-coloured plastics. (Signoret, Caro-Bretelle, Lopez-Cuesta, Ienny, & Perrin, 2020; Becker, Sachsenheimer, & Klemenz, 2017; Rozenstein, Puckrin, & Adamowski, 2017) In the studies, several spectral features are identified that may be used in identifying different polymers that are dyed with carbon black.

However, only one study provided comprehensive testing via developing a calibration or machine learning model with an exclusive validation set. In that study, 280 waste plastic fragments containing ABS, HIPS, PE and PP were studied; the gathered MIR hyperspectral imaging data of half of them were used for training the algorithm and half for testing the developed model. Each class contained around 3000 spectra in training and testing. The F1-score, i.e. the harmonic mean of precision and recall which is often used to denote model performance, was 0.92, indicating a highly accurate model. The tests were conducted using lab-based online prototype measurements. (Jacquin, Imoussaten, Trousset, Perrin, & Montmain, 2020)

Apparently, at least one company, Satake USA, manufactures strictly MIR-based sorter units (Satake USA, n.d.).

3.6.5 Tracer-based sorting

Polymer tracing, or injecting polymers with a tracer material during their processing that can later be identified with a sensor, seems to be an emerging technology in the area of waste sorting. In a very early study from 2000 (Ahmad, 2000), different polymers (PVC, PP, PET and PE) were doped with different UV-fluorescent marker materials. The engineered sorting system consisted of a mercury-arc lamp and four wavelength-selective optical units. The system could reach a 95% purity; according to the researchers, the 5% error rate is due to irregularities in the singulation and air ejection performance, but not the sensor system itself.

More recent studies have demonstrated that the UV-fluorescent tracers work even with black PP plastic, and that some interactions between the polymer and the tracer material may result in quenching of the tracer signal. Moreover, it was demonstrated that using pigments with concentrations below 250 ppm does not result in degradation of mechanical performance. (Maris, Aoussat, Naffrechoux, & Froelich, 2012)

A comprehensive study from 2015 (Brunner, Fomin, & Kargel, 2015) studied 4 UV-fluorescent markers that have an emission signal in the VIS range, on different wavelengths. Different coloured technical plastic (polyoxymethylene, acrylonitrile styrene acrylate and polybutylene terephthalate) flakes that were doped with a combination of markers were used, generating a sample set of 11 different tracer combinations with 1 non-tracer polymer. Each of the 12 classes consisted of 5000 – 10000 plastic flakes that were classified according to the emitted tracer signal using a linear spectral unmixing algorithm. The results were extremely good; average sensitivity and precision were 99.4% and 99.5%, respectively. A continuation study utilized 16 classes (15 tracer combinations and 1 non-tracer polymer) with around 10000 plastic flakes in each class. The average sensitivity and precision with a more advanced classification algorithm were 99.867% and 99.8725%, respectively. (Brunner & Kargel, 2016)

Tracers operating on other wavelengths are available as well. A study from 2020 showed that NIR-active materials that fluoresce on the visible wavelengths (so-called up-conversion fluorescence) could be detected in HDPE matrix even in concentrations as low as 10 ppm when using a highly energetic NIR laser. However, dyeing of the polymer had a crucial effect; carbon black quenches the signal, resulting in no detected emission. (Woidasky, et al., 2020)

XRF has also seen use in tracer-based sorting research. In a study from 2010, PP samples were doped with seven different rare earth oxide tracers. Since these tracers contain elements of high atomic weight, XRF should be able to distinguish them. It was found that 5 out of 7 of these materials could be distinguished; the detection limit was 1000 ppm for 1 minute acquisition time, and 250 ppm for 4 minute measurement.

Recently, a project called HolyGrail focused on providing a proof-of-concept for of using tracer materials in waste sorting facilities. (The New Plastics Economy) Nextek, a company in the project consortium, had previously demonstrated the use of UV-fluorescent tracer materials on the sleeves of plastic packaging. (Packaging Europe, 2020a) Two different tracers were used, one that fluoresced on red and one on blue colour wavelengths. Plastic bottles were equipped with the tracer-imbued sleeve and ran through a sorter accompanying along with non-tracer bottles. The purity and yield of the red tracer fraction was 98% and 93%, whereas for the blue tracer fraction the respective percentages were 100% and 88%.

None of the aforementioned studies have considered the effects and suitability of these tracers on food-grade plastics. As such, the safety of these chemicals, particularly ones containing heavy elements, should be studied.

3.6.6 Digital watermarking

Digital watermarking was also demonstrated in the HolyGrail project. The watermark utilizes subtle variations in the packaging, either by embossing the surface of the polymer itself, or in slight colour modification of the design of the packaging label. Neither of these features are visible to the human eye, but a camera system, equipped with a trained computer vision algorithm, can detect the coded information in these slight variations. As such, these watermarks were demonstrated on the sorting line to be capable of distinguishing watermarked and non-watermarked objects from one another without the use of additional tracers or special dyes or colorants. The distinct benefit of the watermark is that the amount of information can be huge; polymer type, possible additives, food-grade or non-food-grade plastic, bio-based and biodegradability of plastic, the manufacturer, and much more can be encoded in the packaging, enabling an IoT-based (Internet of Things) system. (Digimarc, 2019) However, no accuracies were reported at this stage; a continuation project launched in 2020, HolyGrail 2.0, aims at developing these methods further. (Packaging Europe, 2020b)

3.6.7 Magnetic density separation (MDS)

As the name suggests, MDS utilizes a magnetic field to distinguish between materials of different density. It involves submerging the material to be separated into a liquid containing submicron-sized magnetic particles that, under a magnetic field, generate a density gradient. Materials with different density are submerged at different levels and thus can be separated. MDS has been demonstrated to be rather accurate in separating PE and PP particulates, even if their density slightly overlaps (Ragaert, Delva, & Geem, 2017). The method was used to separate household PP and PE waste flakes into 3 categories based on their density: 1) < 920 kg/m3, 2) 920 kg/m^3 - 930 kg/m^3, and 3) > 930 g/m^3. It was found that class 3) contained only PE, class 2) approximately 95% PE and 5% PP, and class approximately 1) 6.5 % PE and 93.5% PP. (Serranti, Luciani, Bonifazi, Hu, & Rem, 2015) The method may be used to further separate the sink-float-fractions in conventional flotation separation.

There are some commercial separation units available that utilize MDS, for example Liquisort (Liquisort, n.d.) and Umincorp (Umincorp, n.d.). Umincorp purports to be able to produce streams of HDPE, PP and PET with 99% purity in their facility in Amsterdam.

3.6.8 Experimental techniques

Some experimental techniques that have been tested in small scale for plastic sorting and separation are listed here.

3.6.8.1 Magnetic levitation

Magneto-Archimedes levitation is a relatively novel invention, as the effect was invented in 1998 (Ikezoe, Hirota, Nakagawa, & Kitazawa, 1998). It was demonstrated to be able to separate PS, PET and PMMA two years later (Tsunehisa, Shogo, & Masafumi, 2000). Very recently, a more comprehensive study was conducted for waste plastics, namely for separating PP, ABS, PA6, PC, PET and PTFE (Zhao, et al., 2018). These plastics were shredded to different sized flakes and mixed together. Two-staged separation procedure was followed, with two different solvents; the separation results were validated with FTIR. The separation purity was 100%, regardless of particle size.

3.6.8.2 Terahertz imaging & spectroscopy

Terahertz is a term applied to non-ionizing electromagnetic radiation between the infrared and the microwave range; the exact frequency range is debatable, but in the broadest terms it can encompass a range of 100 gigahertz to 30 terahertz (3000 - 1 micrometers) . Terahertz waves can be used for both spectroscopic and imaging modalities, and has been applied e.g. in medical and biological uses (Humphreys, et al., 2004). It has also been applied to the study of plastics; for example, it has been demonstrated in the lab to be able to distinguish different additives in polypropylene (Wietzke, Jansen, Rutz, Mittleman, & Koch, 2007) and identify black-coloured polymers (Nüßler, Pohl, Küls, Hein, & Stein, 2017). There are even commercial equipment available for the latter case (Hailu & Saeedkia, 2016).

3.6.8.3 Fluorescence-based methods

Innovative demonstrations have been recently done via leveraging the fluorescence patterns of plastics. A comprehensive study done in 2019 (Gruber, Grählert, Wollmann, & Kaskel, 2019) utilized a combination of a UV laser and NIR LED illumination to study 12 different plastics, with roughly 400 flakes in each class. The reflectance spectra were captured with a hyperspectral camera, and a convolutional neural network was trained based upon the data. The study found that the plastics could be classified with an average accuracy of 93.5% using support vector machine and convolutional neural network -based algorithms.

The decay of fluorescence seems to be also usable in distinguishing polymers from each other. For example, using time-resolved fluorescence spectroscopy, it was found that PP, PTFE, PA6 and PVDF have a distinct pattern from each other (Gies, Schömann, Prume, & Koch, 2020). Fluorescence lifetime can also be used: detecting the nanosecond range, PA, PET, PP and PVC show clear differences in their respective lifetimes (Wohlschläger, Holst, & Versen, 2020).

3.6.8.4 RFID tagging

Radio-frequency identification (RFID) is a well-established technology that has been considered for the use of waste plastic sorting as well. In a thorough report (Schindler, et al., 2012), the use of RFID was reviewed from many different viewpoints, including the potential effects to sorting of plastics. In order to be implemented to waste sorting framework, the (passive) tags are embedded or printed to the plastic objects, a radio-frequency antenna is used to read the tag e.g. in the sorting facility, and the information in the tag with standardized format is acquired from a database. As the cost-benefit of embedding RFID tags to consumer-use plastic packages is arguably quite poor, the technology has more prospects in other areas, such as electronic devices and automotive components.

3.7 Sensor-based sorting units

Sensor-based sorting is usually done by capturing the response of a material to an electromagnetic signal. In addition to this capture, sensor-based sorting units have different components to execute the whole separation process. This section compacts the information from (Wotruba & Harbeck, 2010) about sensor-based sorting.

In general, sensor-based sorting consists of four steps: presentation, detection, data processing and separation. Presentation means bringing the material stream onto the detector field of view such that individual objects can be subjected to the signal. Detection consists of emitting the signal from the electromagnetic source and capturing the response via the sensor. Data processing is done via computer; in this part, the captured signal is digitized and processed by an algorithm that deduces which material it most resembles on its reference library which it has been calibrated or trained on. Finally, separation is the process of actuating the sorting of individual objects based on the data processing step. Separation can be done e.g. with compressed air; the individual particles are blown to different chambers.

Two types of sensor-based sorting units are most popular: the chute type and the belt type. In belt type sorters, the sensor is located above a conveyor belt upon which the material to be sorted is moving horizontally. In order to actuate the separation, the end of the conveyor belt is equipped with air nozzles that span the width of the belt. The sensor usually divides the material into two, the eject and the reject. The eject material, when identified by the sensor, is blasted with compressed air by the nozzle such that the objects end up in a separate receptacle than the reject, which is not blown by air and consequently drops to its own receptacle. Belt type sorters have been applied for both whole packaging as well as shredded particles.

In chute type sorters, the material is brought down to fall inside a chute, usually via a vibrating conveyor. The sensor is located perpendicular to the chute, and the material is detected as it falls down an incline. After the sensor, the chute splits usually into two chambers, corresponding to the eject and reject fractions; ejection is actuated by air nozzles. Chute type sorters can generally be applied for waste that has been shredded.

As is apparent, the timing of separation by compressed air must be calibrated very accurately based on either the speed of the conveyor belt or the fall down the chute. The spatial accuracy is also key; only the air nozzles on the exact location of the identified object must be discharged so as to prevent the ejection of adjacent items.

In addition to compressed air-based separators, there are also sorters that employ paddles to mechanically move the input material to different fractions, or solutions with water jets. These solutions are slow and inaccurate compared to pneumatic sorters. Moreover, there exist multi-way sorters (sorting into more than two fractions simultaneously) but no research seems to have been conducted on evaluating their performance.

3.7.1 Actuation

Not only do the sensor and the algorithm affect the sorting material purity and yield in sensor-based sorting, but actuating the separation also plays a crucial part. Occupation density, i.e. how much material is covering the sensor detection zone in the conveyor of the sorter also has a great significance. Occupation density and throughput are very highly correlated with each other. In the study by (Küppers, Seidler, Koinig, Pomberger, & Vollprecht, 2020), this feature was manipulated, and the detection performance based on classifying different compositions of 1000 red (reject) and white (eject) LDPE chips with sizes of around 30 mm x 61 mm was evaluated. The VIS-sensor based sorter utilized a conveyor feeding the material down a steep incline, resembling more closely the chute-type sorter than the traditional belt type sorting system. Depending on the composition of the 1000 chips, the eject purity decreased from 100% to 95% with the high-purity (95% white) case as the occupational density increases from 5% to 100%, and with the extremely low purity case (20% white) the performance degraded from 95% to 75%. The effect on eject yield was that, on average, increasing the occupation density from 5% to 95% caused a dramatic drop from 98% to 25%. The performance degradation was due to the errors in the sensor and accompanying algorithm (overlapping particles), as well as due to errors in the mechanical actuation system.

A more recent study by the same research group looked into similar effects on a case more relevant for plastic sorting: classifying PET and polyolefin (PO) particles with NIR hyperspectral imaging using the same chute sorter system. PET was the eject and PO the reject, and 18500 - 34500 such particles from a shredder (< 30 mm) were used. The ground truth of these particles was known beforehand, and they were first brought to the NIR-HSI system to be classified several times (apparently all incorrectly classified particles were removed from the sample set) in order to account only for the effects of mechanical actuation. Several cases were studied, but an interesting finding was related to the effect of input composition to the amount of misclassified reject in the eject stream. The maximum throughput of reject PO in the eject fraction was at input PET composition of 30%, and at 50% the amount was slightly lower than at 20% or 40%. The incorrect classification is explained by eject particles (or the compressed) air entraining reject particles as they are ejected. The purest fraction, on average, was obtained with 50% PET input composition, and the lowest with 5%. As expected from the previous study, the throughput rate had a great impact on both the purity and the yield; the higher the throughput rate and percentage of reject in the input stream, the lower both. The faster the conveyor runs and the more eject there is in the input fraction, the more of the reject there is in the output eject fraction relative to the input reject amount, although a saturation seems to be reached at some point. (Küppers, et al., 2021)

Comparing the two studies, what is clear is that the size of the particles seems to have a great effect. In the former, the particles (were roughly two times larger than in the latter. With the lowest throughput rate (around 175 kg/h) and different input compositions, the eject purities were over 95% with a yield of approximately 98% in all cases in the former study. In the latter, with the lowest throughput rate (15 - 20 kg/h), the purity and yield varied from 67 - 83% and 91 - 99%, respectively, with different input compositions. This would indicate that perhaps with whole containers entraining is not a significant factor of impurities. The numbers of particles, however, were very different, and as such the results are not directly comparable (1000 particles in the former, over 18500 particles in the latter).

Another study by some of the same researchers looked at the effect of surface roughness and moisture of plastic particles on NIR hyperspectral image classification accuracy. They used the same sorting unit but a different sensor. It was found that generally the effect of these features are very small; increased surface roughness lead to very slight increase in classification accuracy due to increased amount of diffused reflectance (thus higher signal-to-noise ratio on the sensor), while increased surface moisture lead to slightly worse classification accuracy. However, increasing the surface roughness lead to some decrease in the sliding speed down of low-softening plastics down the incline, leading to errors due to wrongly timed discharge of compressed air. (Küppers, Schloegl, Oreski, Pomberger, & Vollprecht, 2019)

In a very recent study, the effect of individual object tracking via computer vision on sorting performance was studied. The experimental setup consisted of a chute type sorter with an RGB camera. An object tracking algorithm was used to predict the location of each particle on the air nozzle bar based on acquired high-speed video of the particles falling down the chute. Two tests were conducted: one with two differently coloured wooden plates, and one with two differently coloured lentils. The researchers also compared their method to the baseline, i.e. using a line scanner with no object tracking, in two configurations: one with a small detection window (i.e. only one air nozzle, the one closest to the prediction is discharged) or a large detection window (i.e. also adjacent air nozzles are discharged). The extended window was used also in the tracking phase by enlarging the bounding box of each object. The percentage of particles to be ejected in the 200 gram input stream was 5% in all cases, and a throughput rate of around 5 grams / second was used. It was found that, for lentils, sorting efficiency increased by 20.19 and 7.11 percentage points, and for wooden plates by 11.02 and 1.98 percentage points in the small and large detection window case, respectively. (Maier, et al., 2021)

Similar studies have been conducted for a belt type sorter as well (Pieper, et al., 2016). As compared to a line scanner, an area scanner (i.e. a camera) was used to predict the movement of different shaped particles (spheres, cuboids and cylinders) on a belt before air nozzle separation. The method was based on numerical discrete element modelling, and they found that using an area scanner was vastly better in terms of the percentage of false positives and false negatives for all shapes. The simulation results were later compared to real-life experimental measurements using peppercorns, maize grains and coffee beans; the experiments agreed with the modelling quite well. However, simulating these more complex particles, the number of true positives *and* false negatives were slightly higher in the case of an area scanner as compared to a line scanner. (Pieper, et al., 2018)

As all of these studies employed small particles, it is unclear how much movement whole containers make, and whether or not this has an effect on the sorting performance. In one study, it was recognized that rolling of cylindrical objects on the conveyor belt can degrade the sorting performance (Kleinhans, et al., 2021). Flattening of the plastic containers before sorting can be used to counter this.

As mentioned above for chute sorters, the effects of increasing throughput and input eject percentage leading to decreased separation efficiency have been found for particles on belt sorters in the domain of mining (Pascoe, Udoudo, & Glass, 2010). Moreover, in this study, it was found that the size of particles matters as well: decreasing the particle size leads to worse separation efficiency due to increased possibility of reject particle agglomeration to and overlapping with eject particles, consequently leading to co-ejection. The effect of increased throughput leading to increased probability of overlapping and consequent incorrect ejections had been studied before (De Jong & Harbeck, 2005).

The benefits of computer vision can be significant. The sensor position, of course, plays a role; if the sensor is close to the air nozzle separator, the errors due to line scan movement predictions are most likely smaller. However, the speed of data processing restricts the location; more complex algorithmic operations require more time. In these cases, object tracking and motion prediction based on it can be used to increase the performance.

The pre-processing steps prior to sensor-based sorting has a direct effect downstream. In a recent study using the Redwave 2i NIR sorter in a sorting facility, it was found that the yield of separated 3D plastics (LDPE, HDPE, PET, PU, PS and PVC) from non-plastics and black plastics in streams of mixed municipal and mixed commercial waste increased by 3 - 5 % when drum screen and ballistic separation are used in combination before sensor-based sorting (Möllnitz, Küppers, Curtis, Khodier, & Sarc, 2021). According to the researchers, this is due to the effect of increased friction in the aforementioned pre-processing steps, resulting in a decrease of adhesive fines from material surfaces which facilitates sorting due to cleaner surfaces of plastic. The sorting purity, however, remained the same.

3.7.2 Technology readiness level of the solutions

In the above sections, the state-of-the-art and novel technology solutions for waste sorting were listed. Moreover, the actuation performance of sorting units and their bottlenecks have been studied as well. In Table 3, a review of sorting units with the aforementioned technologies are given. The use cases, the technology readiness levels (TRL) of each solution as well as implementation requirements and throughput rate in commercial sorting units are listed. As the sorting units are tailored for either whole containers or flakes, the throughput rate of both solutions are listed where available. The TRL levels are estimates by the authors based on openly available data, and are based on the scale by the European Union (European Union, n.d.):

- TRL 1 – basic principles observed
- TRL 2 – technology concept formulated
- TRL 3 – experimental proof of concept
- TRL 4 – technology validated in lab
- TRL 5 – technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies)
- TRL 6 – technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies)
- TRL 7 – system prototype demonstration in operational environment
- TRL 8 – system complete and qualified

- TRL 9 – actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies; or in space).

Table 3. Estimated technology readiness levels of each solution in waste sorting units. The use cases as well as restrictions, implementation requirements and throughput rates are listed as well. The TRL scale is in the range 1- 9.

Method	Use case	Restrictions	Implemen-tation require-ments	TRL	Throughput rate
NIR spectro-scopy	polymer sorting	not applicable to black plastics	already available	9	whole containers: 0.5 - 10 t/h flakes: 0.2 - 9 t/h[1]
VIS spectro-scopy	colour sorting	-	already available	9	whole containers: 0.8 - 10 t/h flakes: 0.6 - 6 t/h[1]
CCD camera	colour and shape sorting	-	already available	9	whole containers: 0.5 - 9 t/h flakes: 0.2 - 9 t/h[1]
XRF spectro-scopy	screening of heavy elements	requires shielding	already available	9	flakes: for glass, 28 t/h[2]
NIR-HSI	polymer sorting	not applicable to black plastics	already available	8	whole containers: 15 t/h[3], 10 t/h[4]
MIR spectro-scopy	polymer sorting; also black plastics	-	-	7	**purely MIR based sorter data not available**
MIR-HSI	polymer sorting; also black plastics	-	-	7	**for sorter units, data unavailable;** flakes (2 x 2 cm): 18 t/h[5]
MDS	polymer sorting based on density	requires shredding plastics	requires flotation & magnetic particles	6	1.5 t/h[6]
tracer	polymer sorting, BRF vs no BFR, foodgrade	requires redesigning packaging	requires VIS or	6	N/A; same as VIS or CCD camera

[1] (4R Sustainability Inc., 2011)
[2] (REDWAVE (c), n.d.)
[3] (Machinex)
[4] (GreenEye, 2020)
[5] (Specim, 2019)
[6] (Umincorp, n.d.)

	vs. non-foodgrade…		CCD camera		
Raman spectro-scopy	polymer sorting	accurate focusing needed	-	6	whole containers: 0.1 - 0.4 t/h[7] flakes (**conventional Raman based sorters not available**): 2.4 - 3 t/h (Powersort 200), up to 10 t/h (Powersort 360)[8]
LIBS	polymer sorting, screening of heavy / light elements	accurate focusing needed; point measurement only at the moment	-	4	**data for plastics unavailable;** for metals: 5 t/h[9], several t/h[10]
water-marking	polymer sorting, BRF vs no BFR, foodgrade vs. non-foodgrade…	requires redesigning packaging	requires CCD camera	**unknown;** estimation: 4	N/A; same as CCD camera

4. Summary

This report gave an overview of the recycling scheme existing in Finland from the viewpoint of post-consumer plastic packaging sorting, a brief review of the state-of-the-art, and a survey on novel technologies that potentially can be used to bridge the gaps in the existing sorting framework. Moreover, the performance of sensor-based sorting units have been evaluated and bottlenecks therein established.

The limitations of NIR spectroscopy, arguably the most commonly used technique in sensor-based sorting units in material and plastic recovery facilities, include the inability to identify black and multilayer plastics, and the high possibility of false identifications due to label sleeves or other materials overlapping the target object. These problems have been shown to be solvable using different sensor technologies: the spectrum from black plastics are not quenched in the MIR range; multilayer materials can potentially be distinguished using laser-based methods such as LIBS and Raman spectroscopy; the probability of false identification decreases vastly when an imaging-based tool, such as NIR HSI, is used, as the identification is not based on a single point spectrum but rather an area of individual spectra spanning the whole object.

[7] (Saimu Corporation, n.d.)
[8] (Unisensor, 2017)
[9] (Toratecnica, 2019)
[10] (Steinert, 2016)

On top of problems with the sensor, the actuation performance in sensor-based sorting units is also imperfect. The composition of material input to the sorter has a complex effect on the separation performance: the yield and purities are very dependent on what percentage of the input material is to be ejected by the sorter, as the ejection by pneumatic air may entrain reject objects together with the eject. Moreover, the granularity of the material matters as well: the smaller the objects, the greater the amount of impurities in the eject fraction. In some cases, computer vision may be used to increase the sorting performance: smaller particles may move around during the transportation on the conveyor or chute after sensor-based detection and localization, triggering the air ejection in incorrect location. Tracking each individual particle and predicting their motion has been shown to increase the purity and yield of the output.

The use of AI methods in classification tasks has been shown to yield great benefits, particularly in the case of RGB camera data. Instead of utilizing spectral information, wastes of different material can quite accurately be identified based on photographic images using convolutional neural networks. The same approach can also be used for sorting based on colour. Artificial neural network and machine learning -based models have also been applied to spectral data, facilitating better performance as compared to traditional chemometric techniques. The use of neural networks, however, requires vast amounts of data for training the algorithm, which is often a bottleneck in implementing these solutions.

For economically feasible performance, the sorting facilities should be able to produce output on a rather high rate; the largest facilities in Europe have an annual throughput rate of 80 - 120 kt. However, as the sorters' throughput rate are increased, the purity and yield of the sorters decrease. As such, it is clear that a compromise has to be made between the output purity and the throughput. However, very little research seems to have been conducted in evaluating the output and reject fractions of material and plastic recovery facilities around Europe. Conducting comprehensive studies in this domain would be beneficial in order to more clearly see where and why the current sorting and separation technologies fail. Nonetheless, increasing the number of sorters and performing treatments that clean the surface of the individual objects are ways to increase the sensor-based sorting performance and ultimately the output of recovery facilities in terms of purity and yield, respectively.

What comes to the sensor solutions, NIR HSI and RGB cameras seem to be the most potential in facilitating sorting of post-consumer plastic packaging, as they also allow for high throughput in sensor-based sorting units. In addition to the previously mentioned sorting tasks, when coupled with tracer or watermarking of plastic objects, RGB cameras can be used for e.g. distinguishing between foodgrade and non-foodgrade plastic packaging. NIR HSI can be used to expand upon the performance of NIR spectroscopy by tackling some of its inherent challenges. The laser-based techniques Raman spectroscopy and particularly LIBS still require development in order to be feasible in sensor-based sorting units for plastics, even if their benefits in allowing for deeper probing of the object are established.

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