

This document contains the draft version of the following paper: Gundupalli, S.P., Hait, S., and Thakur, A., A review on automated sorting of source-separated municipal solid waste for recycling. Waste Management, first published on September 20, 2016 <http://dx.doi.org/10.1016/j.wasman.2016.09.015>. Readers are encouraged to get the official version from the journal's web site or by contacting Dr. Atul Thakur ([athakur@iitp.ac.in](mailto:athakur@iitp.ac.in)).

# A Review on Automated Sorting of Source-separated Municipal Solid Waste for Recycling

Sathish Paulraj Gundupalli <sup>a</sup>, Subrata Hait <sup>b</sup>, Atul Thakur <sup>c,\*</sup>

<sup>a,c</sup>*Department of Mechanical Engineering*

<sup>b</sup>*Department of Civil and Environmental Engineering*

*Indian Institute of Technology Patna, Bihta, Patna, Bihar 801103, India*

---

## Abstract

A crucial prerequisite for recycling forming an integral part of municipal solid waste (MSW) management is sorting of useful materials from source-separated MSW. Researchers have been exploring automated sorting techniques to improve the overall efficiency of recycling process. This paper reviews recent advances in physical processes, sensors, and actuators used as well as control and autonomy related issues in the area of automated sorting and recycling of source-separated MSW. We believe that this paper will provide a comprehensive overview of the state of the art and will help future system designers in the area. In this paper, we also present research challenges in the field of automated waste sorting and recycling.

*Keywords:* source-separated municipal solid waste, automated waste sorting, recycling, waste recovery, sensors, robotics

---

---

*Abbreviations:* ABS, acrylonitrile butadiene styrene; ACQ, alkaline copper quat; ADC, analog digital converter; Al, aluminum; As, arsenic; Au, aurum (gold); CCA, chromate copper arsenate; CCD, charge coupled devices; CBR, case-based reasoning; C&D, construction and demolition; C/H, carbon and hydrogen; CMOS, complementary metal oxide semiconductor; Cr, chromium; Cu, copper; DAQ, data acquisition; DE-XRT, dual energy X-ray transmission; DNA, deoxyribonucleic acid; EDXRF, energy dispersive X-ray fluorescence; EMS, electromagnetic sensor; FUSSER, fuzzy spectral and spatial classifier; GDP, gross domestic product; HDPE, high-density polyethylene; HIPS, high impact polystyrene; HIS, hue saturation and intensity; HSI, hyperspectral imaging; ICA, independent component analysis; KNN, k-nearest neighbor; LDPE, low-density polyethylene; LED, light-emitting diode; LIBS, laser induced breakdown spectroscopy; LIPS, laser induced plasma spectroscopy; MDS, magnetic density separation; Mg, magnesium; MIR, midrange infrared; MSW, municipal solid waste; Nd:YAG, neodymium-doped yttrium aluminium garnet; NdFeB, neodymium magnets; NF, non-ferrous; Ni, nickel; NIR, near infrared; OCC, old corrugated cardboard; ONP, old news paper; Pb, lead; PC, polycarbonate; PCA, principal component analysis; PE, polyethylene; PET, poly(ethylene terephthalate); PLA, polylactide; PPP, purchasing power parity; PP, polypropylene; PS, polystyrene; PSW, plastic solid waste; PVC, poly(vinyl chloride); PU, processing unit; SS, stainless steel; SVS, smart vision system; RGB, red green blue; Rx, receiver; Tx, transmitter; UNEP, united nations environment programme; UV, ultraviolet; VIS, visual image spectroscopy; WP, white paper; XRF, X-ray fluorescence; XRT, X-ray transmission; Zn, zinc; 3D, three-dimensional.

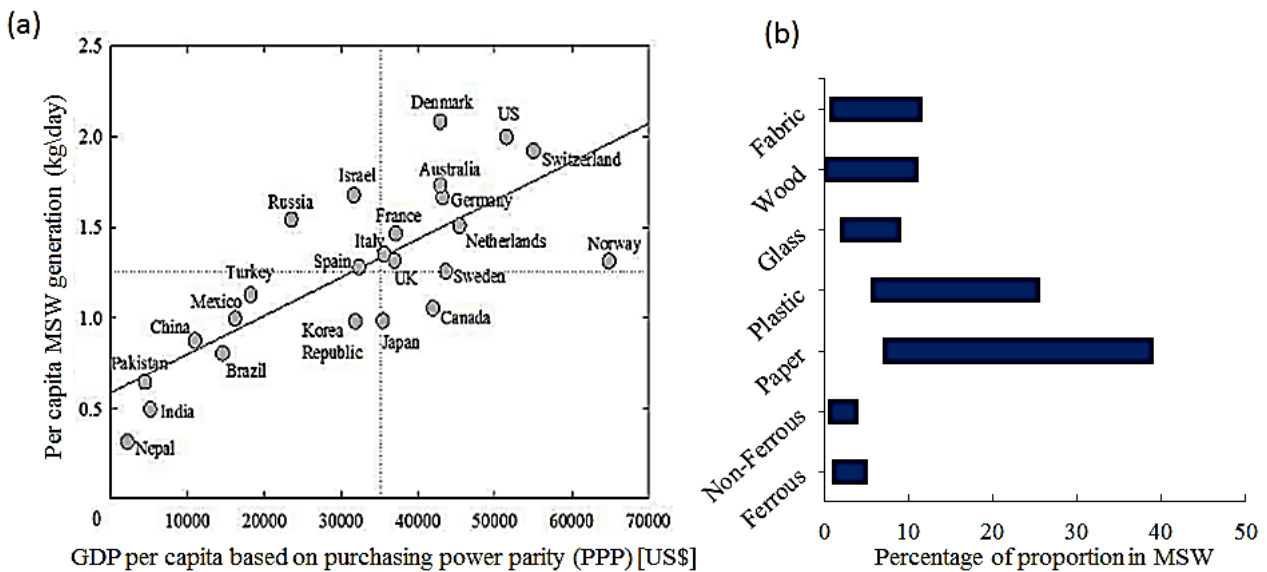
\* *Corresponding author*

\**Tel:* +91-612-3028158; *E-mail* addresses: <sup>a</sup>[sathish.pme14@iitp.ac.in](mailto:sathish.pme14@iitp.ac.in), <sup>b</sup>[shait@iitp.ac.in](mailto:shait@iitp.ac.in), <sup>\*</sup>[athakur@iitp.ac.in](mailto:athakur@iitp.ac.in)

# 1. Introduction

Rapid urbanization and industrialization is causing an unprecedented rise in the generation of municipal solid waste (MSW) worldwide (Chiemchaisri et al., 2007; Liu and Wu, 2010; Saeed et al., 2009). Countries with a relatively higher GDP tend to produce a larger quantity of MSW (see Fig. 1(a)). Projections show that the generation of MSW across major metropolitan cities worldwide will rise from 1.3 billion tonnes in 2012 to 2.2 billion tonnes in 2025 (Hoornweg and Bhada-Tata, 2012; Kawai and Tasaki, 2016). MSW is often a rich source of various useful recyclable materials such as metal, paper, plastic, and glass (see Fig. 1(b)). Effective MSW management can enable recovery of valuable recyclable materials and reduction of negative environmental impact. Waste sorting is a key step in MSW management for the recycling of materials. Researchers worldwide have been actively exploring automated sorting techniques for efficiently processing increasing quantities of MSW. This paper summarizes developments that have taken place in the last decade in the area of automated sorting and recycling of source-separated MSW.

At the waste collection stage, source segregation is often performed for a preliminary sorting of recyclables. The practice of source segregation may not be followed uniformly at all the locations and the extent of required sorting may vary. Developing countries seldom practice source segregation. In this review, we assume that the practice of source segregation is performed and thus the input to the automated waste sorting process is source-separated MSW.



**Fig. 1.** (a) Per capita MSW generation versus GDP per capita based on purchasing power parity. (b) Proportion of recyclables in MSW. Source: (ADB, 2013; Annepu, 2012; Badgie et al., 2012; Banar et al., 2009; Burnley, 2007; Damanhuri et al., 2014; Edjabou et al., 2015; EOCSSB, 2012; EPA, 2014; Hoornweg and Bhada-Tata, 2012; Khatib, 2011; Masood et al., 2014; MfE, 2009; Montejo et al., 2011; OECD, 2012; Paul Randell, 2014; Sharma and McBean, 2007; UNEP, 2012)

Following some early patents filed by Holloway (1989) and Roman (1992), many other automated solid waste sorting techniques have been reported by archival journals and technical conferences. Several review articles have been reported frequently in areas related to automated/semi-automated waste sorting for recycling and are as follows:

- [Dodbiba et al. \(2004\)](#) surveyed various sorting techniques for separating plastic materials. The review primarily focused on non-sensor based design, development, and testing of wet and dry based separating/sorting techniques.
- [Shapiro and Galperin \(2005\)](#) reviewed various air classification techniques for solid particles.
- [Al-Salem et al. \(2009\)](#) reviewed chemical recycling and energy recovery from plastic solid waste (PSW).
- [Sadat-Shojai and Bakhshandeh \(2011\)](#) reviewed energy recovery, mechanical and chemical recycling and separation methods by recycling Poly(vinyl chloride) (PVC) waste.
- [Gaustad et al. \(2012\)](#) surveyed physical and chemical separation methods in sorting and removal of impurities from aluminum debris.
- [Wu et al. \(2013\)](#) reviewed triboelectrostatic separation techniques for sorting plastic from waste.
- [Rahman et al. \(2014\)](#) reviewed sorting techniques to segregate waste paper and also recommended low cost sorting techniques corresponding to the paper type present in the waste.
- [Cimpan et al. \(2015\)](#) reviewed physical processing of waste to segregate recyclables from MSW. The review mainly focused on case studies of operational experience without emphasizing many aspects of automation including material handling, sensors and control.
- [Wang et al. \(2015\)](#) published a comprehensive review on flotation separation of various types of plastics from waste.

This paper provides a comprehensive overview of the state of the art in the field of automated sorting of source-separated MSW for the purpose of recycling. This paper is intended to help designers of automated waste sorting systems select suitable technologies such as sensors, actuators, control algorithms, and sorting processes for recycling source-separated MSW. This review presents a detailed discussion on various comminution and sorting techniques used for segregating recyclable materials. The paper also presents a detailed discussion on the variety of materials that can be sorted as well as the sensors and material handling systems used. In addition, classification rates obtained by various sorting techniques reported in the literature in the last decade are detailed. A detailed discussion on the levels of automation implemented in the waste sorting systems is presented. This review also identifies open research issues and suggests future research directions in the field of automated waste sorting.

A large number of research papers are reported in the area of automated source-separated MSW sorting and thus it is very difficult to include all of them in this paper due to space constraints. We have thus categorized and organized the literature based upon comminution process, direct sorting, and indirect sorting. The scope of this review paper is listed below.

- The main focus of this paper is to survey the state of the art automated sorting techniques for recovering various recyclable waste fractions like metal, plastic, paper, glass and wood from source-separated MSW. However, some of the techniques discussed in this paper

may also be applicable to other waste streams such as industrial waste, electronic waste, and construction and demolition waste. Henceforth, we refer to ‘source-separated MSW’ as ‘MSW’ for the sake of brevity.

- This paper mainly surveys journal and conference publications during the period 2004–2015.
- This paper compares the sorting techniques reported in the literature in terms of diversity of materials sorted, accuracy of sorting, speed of operation, robustness, flexibility, and reliability.

## 2. Automated sorting techniques for various MSW fractions

Automated waste sorting techniques can be categorized into two types: direct sorting and indirect sorting. Direct sorting techniques utilize material properties like magnetic susceptibility, electrical conductivity and density for heavy media separation by applying external fields like magnetic, eddy current and gravity respectively (Gaustad et al., 2012; Mesina et al., 2003; Svoboda, 2004). Indirect sorting, on the other hand, employs sensors to detect the presence and often the location of recyclables in the waste so that automated machines or robots can be employed to sort the detected recyclable materials.

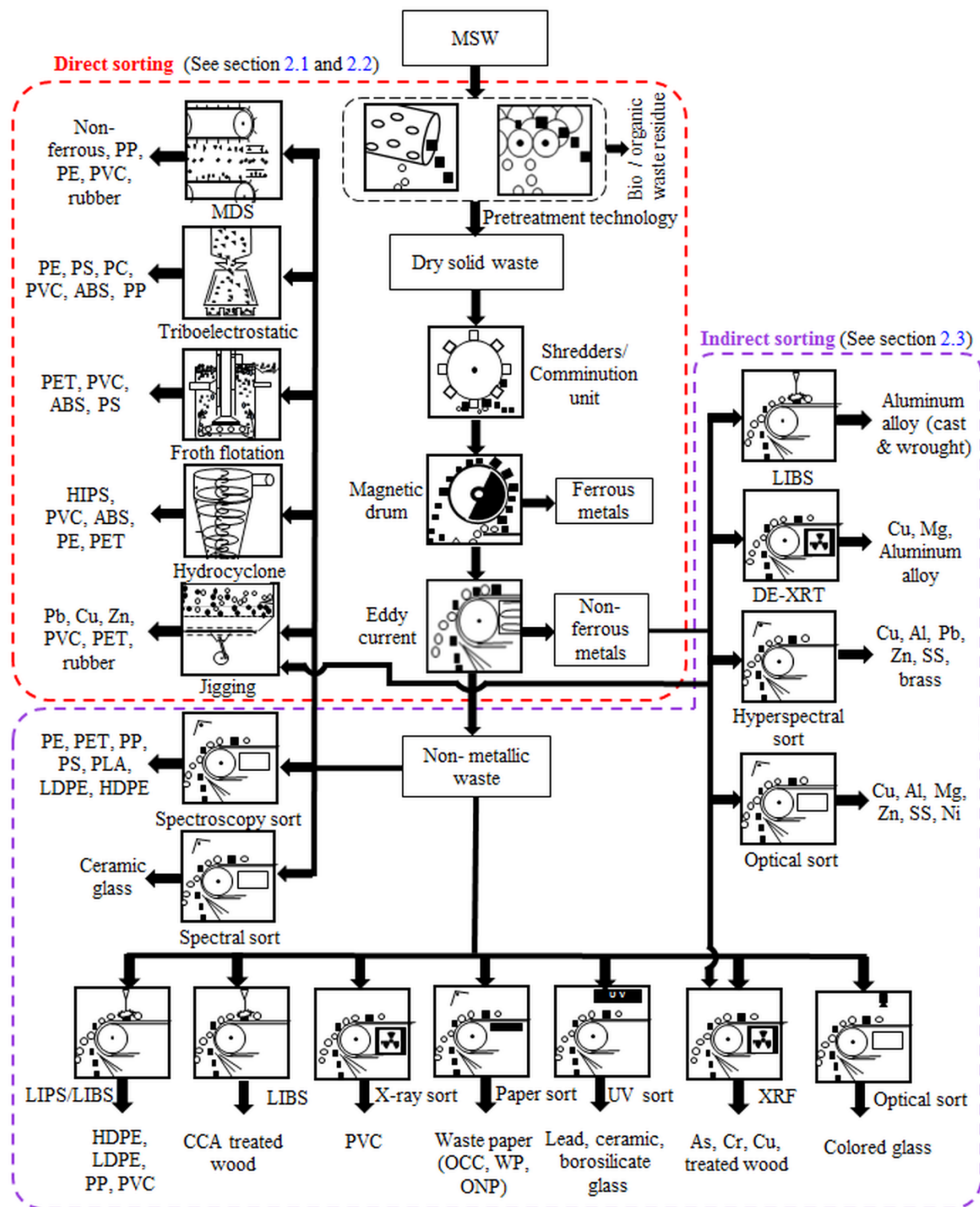
**Table 1**  
Various sorting techniques based upon composition of waste

	Sorting Technique																	
	Direct sorting (See section 2.2 [a-m])											Indirect sorting (See section 2.3.1-2.3.5)						
	Screw-press (a)	Disc-screen (b)	Shredder + Magnet (c)	Magnetic drum (d)	Magnetic head pulley (e)	Magnetic Overhead belt (f)	Eddy current (g)	Magnetic density separation (h)	Triboelectrostatic (i)	Hydrocyclone (j)	Jigging (k)	Froth flotation (l)	Air separator (m)	Eddy current (2.3.1)	LIBS (2.3.2)	X-ray sort (2.3.3)	Optical sort (2.3.4)	Spectral sort (2.3.5)
Material	Organic waste	✓	✓	✓	✓	✓												
Ferrous metal			✓	✓	✓	✓					✓							
Non-ferrous metal							✓	✓	✓		✓			✓	✓	✓	✓	✓
Plastic								✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Paper													✓					
Glass																	✓	✓
Wood															✓	✓		

Table 1 lists various sorting techniques and their applicability to different types of recyclable materials such as metals (ferrous and non-ferrous), plastic, paper, glass, wood and organic waste. Direct sorting techniques are discussed in details in Section 2.2 while indirect sorting techniques in Sections 2.3.1-2.3.5.

Fig. 2 illustrates the entire process flow of automated sorting of recyclable materials from MSW. Initially, pre-treatment is performed using screw press, disc screen, and shredder + magnetic techniques. After this, dry waste is obtained and later dry waste fraction is subjected to comminution or shredding processes that include swing-hammer shredder, rotating drum, alligator shears, hammer mill, ring mill, shear shredder and impact crusher based techniques. In order to

sort ferrous materials, magnetic drum techniques are used. After this, non-ferrous metals are sorted using various indirect sorting techniques like eddy current, LIBS, DE-XRT and optical sort and hyperspectral sort.



**Fig. 2.** Flow diagram of automated sorting of recyclables from MSW. First, MSW is processed via pre-treatment (sorting organics from dry waste fraction) techniques. Then the dry waste fraction is subjected to comminution and shredding processes. This is followed by sorting metallic waste fraction from non-metallic waste fraction. After this, non-metallic waste fraction is sorted into its various constituents.

## 2.1. Comminution techniques

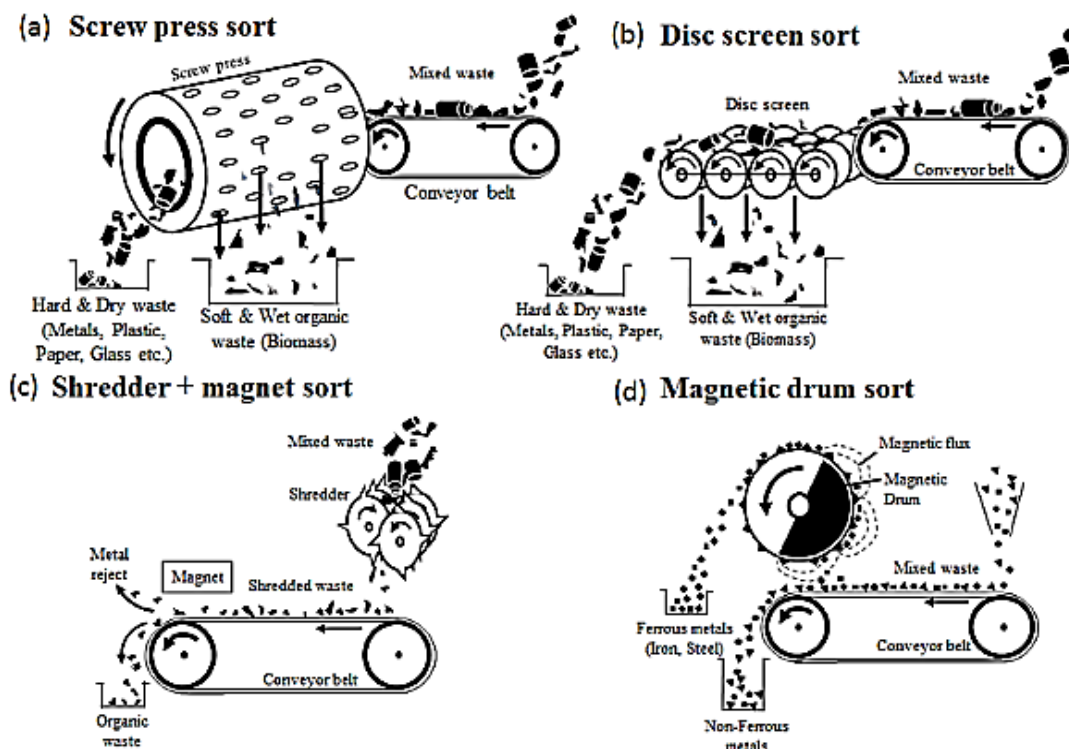
Bulk waste material is pulverized into particles of uniform size using forces produced by pressure, impact, cutting or abrasion during comminution, for convenient handling and to remove contaminants (Bonifazi and Serranti, 2012; Buchan and Yarar, 1995; Kasper et al., 2015). Some commonly used tools for comminution of MSW are swing hammer shredders, rotating drums, alligator shears, hammer mills, ring mills, shear shredders, and impact crusher.

## 2.2. Direct sorting

This section presents various direct sorting techniques used for MSW.

(a) **Screw press:** In the screw press pre-treatment technique (shown in Fig. 3(a)), the organic waste fractions are squeezed through narrow slits resulting in segregation of soft and wet fractions from plastic, paper, wood, animal bone and metal (Hansen et al., 2007; Jank et al., 2015).

(b) **Disc screen:** In this technique, the rotating discs are equally spaced in a chamber (see Fig. 3(b)), where the small and heavy organic waste fractions fall between the discs, while the light and large fractions are transported towards the edge of the disc (Hansen et al., 2007; Jank et al., 2015).



**Fig. 3.** Various direct sorting techniques for pre-treatment of MSW. (a) Screw press sorting technique. (b) Disc screen sorting technique. (c) Shredder + magnetic sorting technique. (d) Magnetic drum sorting technique.

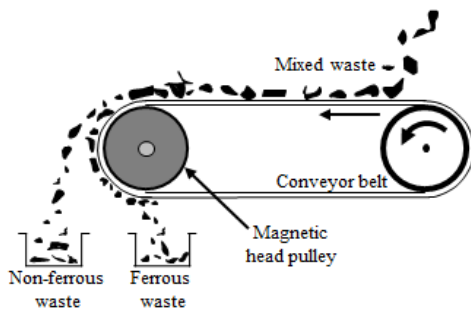
(c) **Shredder along with magnet:** The combination of shredder and magnet is utilized for sorting paper and organic matter from MSW stream (see in Fig. 3(c)) (Hansen et al., 2007). The input

stream of this technique must be free from plastic contaminants. With this technique the recovery rate of bio-waste was approximately 98% free from metal contaminants (Hansen et al., 2007).

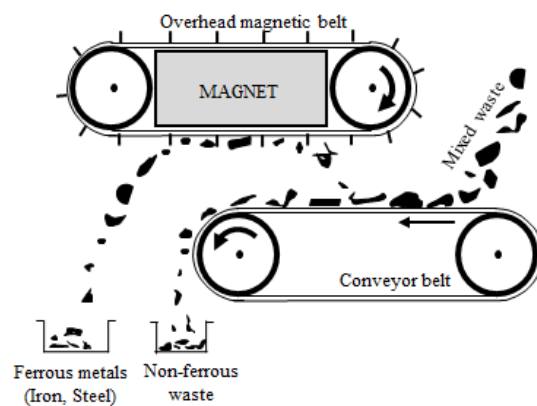
(d) **Magnetic drum:** The magnetic drum technique segregates ferrous fractions from non-ferrous and other mixed waste fractions by measuring the magnetic susceptibility of waste (Kelland et al., 1974; Svoboda and Fujita, 2003). The magnetic drum consists of a stationary permanent magnetic assembly placed on one half of its circumference as shown in Fig. 3(d). As the mixed waste is supplied, the powerful magnetic flux attracts and holds the ferromagnetic material to the revolving shell. The revolving shell carries the ferrous fractions to the far edge of the drum and collects them into respective bins (See Fig. 3(d)) (Oberteuffer, 1973; Ohara et al., 2001; Svoboda, 2004). Magnetic drum based techniques are incapable of distinguishing between various non-ferrous metal fractions.

(e) **Magnetic head pulley:** The magnetic head pulley technique segregates ferrous waste fractions from non-ferrous. The mixed waste is transported through a material handling system (conveyor belt) near to a magnetic head pulley. Ferromagnetic waste fractions are held by the magnetic belt while other non-ferromagnetic fractions are discharged (see Fig. 4(e)) (Bonifazi and Serranti, 2012).

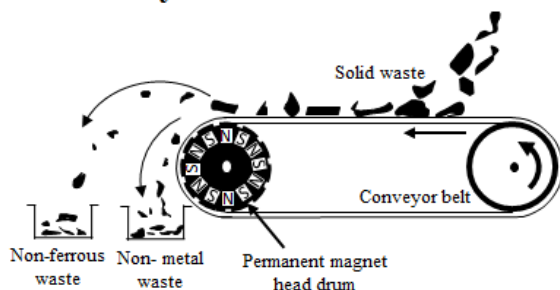
(e) **Magnetic head pulley sort**



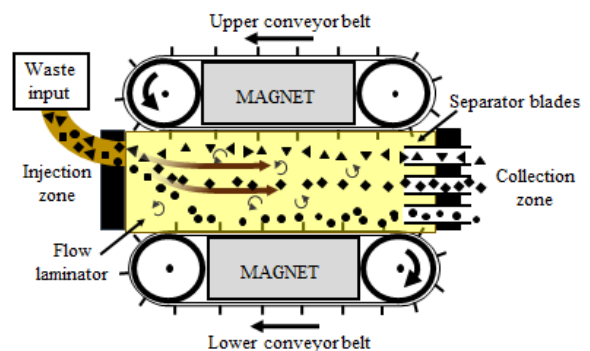
(f) **Magnetic overhead belt sort**



(g) **Eddy current sort**



(h) **Magnetic density separation (MDS)**



**Fig. 4.** Various direct sorting techniques for pre-treatment of MSW. (e) Magnetic head pulley sorting technique. (f) Magnetic overhead belt sorting technique. (g) Eddy current sorting technique. (h) Magnetic density separation.

**(f) Magnetic overhead/Cross belt:** The magnetic overhead/cross belt technique segregates ferrous waste fractions from mixed waste stream. The magnetic overhead belt has a magnetic field acting normal to the direction of mixed waste flow (shown in Fig. 4(f)). Thus, the metal pieces are attracted and removed from mixed waste. The metal pieces are subsequently discharged to a collection bin via a moving belt (Bonifazi and Serranti, 2012).

**(g) Eddy current:** The segregation is performed using a rotary drum type separator. The rotary drum is in-line with Neodymium magnets (NdFeB) with alternating North and South poles as shown in Fig. 4(g). A thin layer of a mixture of non-ferrous metal fractions (ferrous fractions are separated beforehand using other techniques) and non-metallic waste is transported towards the rotary drum using a conveyor system (Bonifazi and Serranti, 2012; Gaustad et al., 2012; Krivtsova et al., 2009; Rem et al., 1998). The external magnetic flux repels the non-magnetic electrically conductive metal fractions from the mixed metal waste. This technique has a low operating cost and yields a high degree of purity of recovered metal. This technique however is not designed for sorting metals that may become hot in an eddy current field as that may lead to damage of the separator.

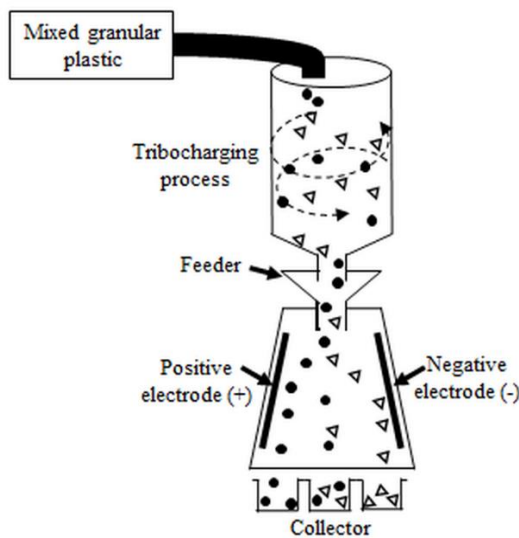
**(h) Magnetic density separation (MDS):** The MDS technique utilizes magnetic liquid (ferrofluid) as the separation medium. Waste input is mixed with the magnetic liquid and introduced into a separation zone as shown in Fig. 4(h). Large magnets are used for creating a magnetic field. The magnetic field reduces exponentially with the distance from the magnet. Due to the magnetic field, the effective density of the magnetic fluid gets altered (Bakker et al., 2009; Hu, 2014; Luciani et al., 2015; Muchova et al., 2009; Rem et al., 2012). By varying the density of the magnetic fluid present in the waste input, the constituent recyclable polymeric materials of different densities can be made to float at different levels (Hu, 2014; Luciani et al., 2015). The floating polymeric materials are then collected via separator blades (see right side of Fig. 4(h)).

**(i) Triboelectrostatic separation:** Triboelectrostatic separation process is used for sorting plastics. The physical phenomenon used for sorting is ‘contact electrification’ or ‘frictional electrification’ (Lowell and Rose-Innes, 1980). When mixed waste is passed through a tribocharging chamber, shredded plastic present in the waste gets charged with different polarities by friction electrification (see Fig. 5(i)). The charged pieces of the mixed waste are then passed through an electric field to separate them. The trajectory of each piece of waste is determined by the amount of charge carried. The electric field is so designed that the pieces of shredded plastic materials fall into respective bins (Li et al., 2015; Wu et al., 2013).

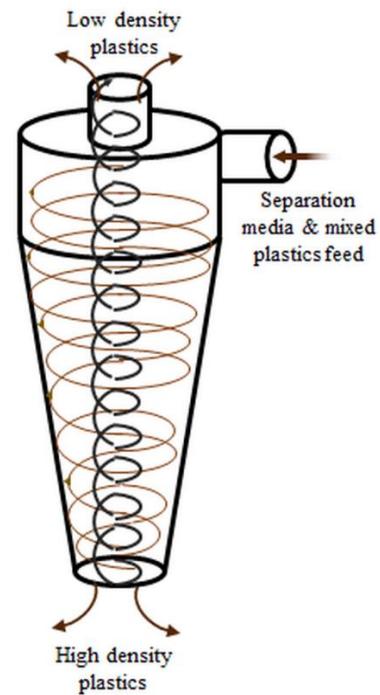
**(j) Hydrocyclone:** Hydrocyclone utilizes centrifugal force for density separation (see Fig. 5(j)). The technique can be used for the separation of materials like ABS (Acrylonitrile butadiene styrene), PE (Polyethylene), HIPS (High impact polystyrene), and PVC (Poly (vinyl chloride)). Various factors influencing the liquid separation of a given material are its variation in density (from fillers, pigments, porosity, etc.), wettability, shape factors of size-reduced particles and level of liberation from other materials (Al-Salem et al., 2009; Richard et al., 2011; Yuan et al., 2015).

**(k) Jigging:** Jigging is a gravity concentration technique for sorting, which works based on the interaction of buoyancy, drag, gravity, and acceleration. In this process the solid-water mixture is placed into a perforated vessel called a pulsatile bed (de Jong and Dalmijn, 1997). In a wet jig bed, the bed is shaken (“jigged”) to induce vertical currents in the water column, which lifts the solid particles (see Fig. 5(k)). The currents can be of two types: ascending current and descending current (Pita and Castilho, 2016). Materials with higher density get settled at the bottom. Segregation is performed according to the material density, size, and shape. The main parameters that affect the jigging process are: jig stroke length, initial bed height and jigging speed (Cazacliu et al., 2014; de Jong and Dalmijn, 1997; Li et al., 2007; Pita and Castilho, 2016).

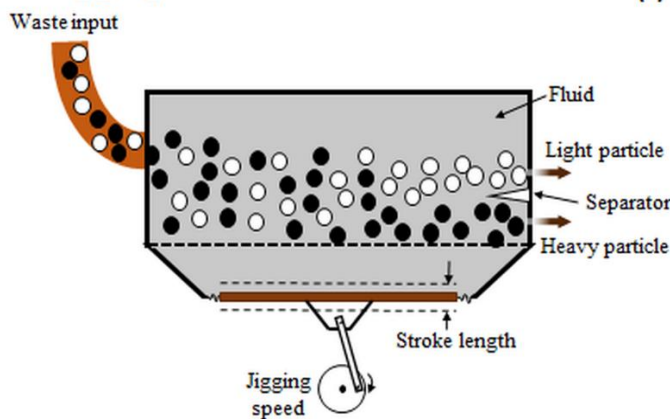
**(i) Triboelectrostatic separator**



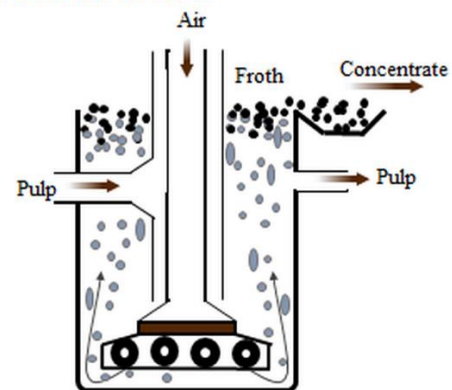
**(j) Hydrocyclone**



**(k) Jigging**



**(l) Froth flotation**



**Fig. 5.** Various direct sorting techniques for pre-treatment of MSW. (i) Triboelectrostatic separator. (j) Hydrocyclone based sorting. (k) Jigging based sorting. (l) Froth flotation based sorting.

**(l) Froth flotation:** The froth flotation technique utilizes the hydrophobicity of plastic to separate it from the waste stream. Before processing, the waste is shredded into fine particles or pulp using

a comminution process (Fraunholz, 2004; Wang et al., 2015) and mixed with water. A schematic diagram of froth flotation is depicted in Fig. 5(l). In this process, air is dissolved in the mixture of water and the waste pulp under high pressure. The dissolved air is then released into a flotation section at atmospheric pressure. This leads to the formation of froth on the surface of water-waste mixture. The suspended plastic particles, due to their hydrophobicity, get attached to the bubbles in the froth thus formed. The combined specific gravity of the bubbles carrying plastic particles is less compared to the fluid medium resulting in flotation. This flotation is used for separating plastic from the water-waste mixture (Patachia et al., 2011; Takoungsakdakun and Pongstabodee, 2006; Vajna et al., 2010; Wang et al., 2012, 2014).

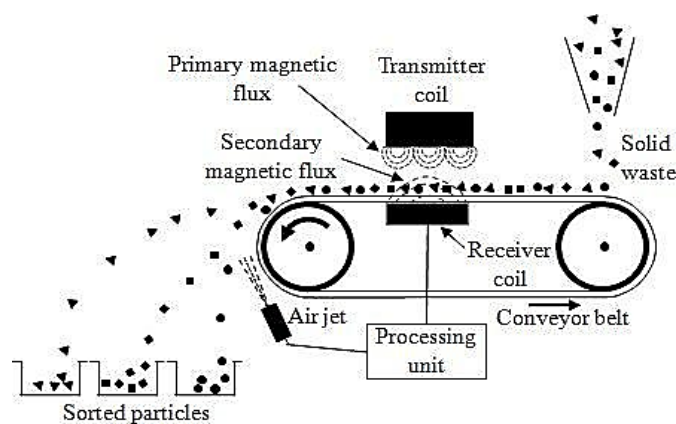
**(m) Air separator:** A compressed air nozzle is used for preliminary recovery of light non-metallic fractions (e.g., polymers, paper, foam, rubber, fibers, etc.) from previous processes, like magnetic sorting and eddy current type separation (Bonifazi and Serranti, 2012). A compressed air nozzle is used to release high pressure air jet to impart a force of separation on the mixed waste sample. Lighter particles get blown away to a larger distance while the heavier ones to a shorter distance. Separation is thus performed by keeping separate bins at various distances from the air nozzle for collecting the particles of differing weights.

### 2.3. Indirect sorting

Sensors are used for detecting recyclable materials in the bulk input waste followed by segregation using various actuators in indirect sorting.

#### 2.3.1. Eddy current based sorting

Electromagnetic sensor (EMS) is utilized for detection of non-ferrous metal fractions based upon electrical conductivity of the sample in eddy current based sorting (Braam et al., 1988; Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012; SchlÄumann, 1975). When a magnetic flux generated by an electromagnetic coil is passed through a conductive test material



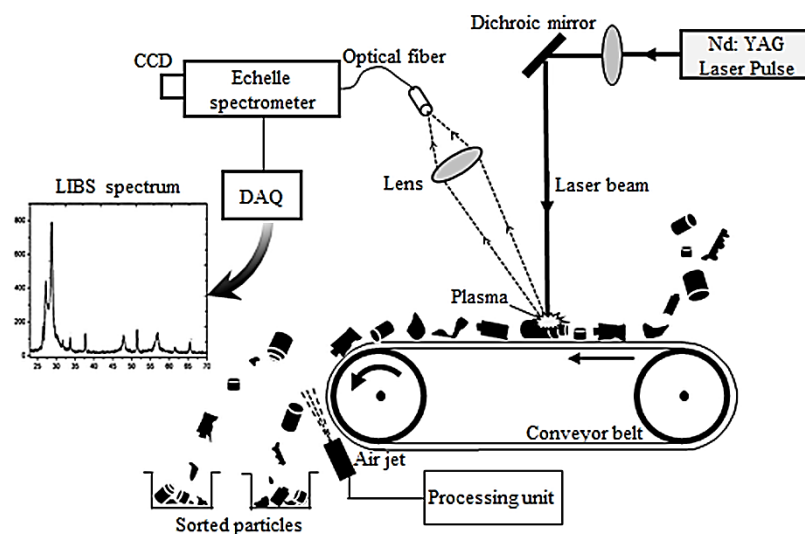
**Fig. 6.** Eddy current based sorting technique consisting of sensor unit for detection of NF metals and processing unit for ejection of various MSW waste fractions.

then an eddy current is induced (Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012). Fig. 6 depicts the process of eddy current based sorting technique. A transmitter coil is suspended over the conveyor system and a receiver coil is fixed beneath the belt. An alternating

current is supplied to the transmitter coil. A primary magnetic flux is produced in the axial direction of the transmitter coil. As the test materials are passed on a conveyor belt underneath the transmitter coil, an eddy current flows into the test material. According to the Lenz's law, the generated eddy current opposes the secondary magnetic flux as shown in Fig. 6 (Mesina et al., 2003; Rahman and Bakker, 2012). By measuring the secondary flux, the presence of ferrous metals in bulk waste is detected. Compressed air jet is then used for segregating the detected ferrous materials into their respective bins (see Section 2.2.(m)). The parameters that affect the process of eddy current based sorting include electrical conductivity and magnetic permeability (Kutilla et al., 2005; Mesina et al., 2003).

### 2.3.2. Laser Induced Breakdown Spectroscopy (LIBS)

Laser Induced Breakdown Spectroscopy (Noll et al., 2001, 2008) utilizes a high power laser pulse. Los Alamos National Laboratory in collaboration with Metallgesellschaft were the pioneering group that developed the LIBS system in 1990 for the identification of metallic waste (Sattler, 1990; Sattler and Yoshida, 1993). LIBS provides high dimensional spectrometric information for the analysis of metal alloys (Grzegorzek et al., 2011), plastics (Gondal et al., 2007) and treated wood waste (Solo-Gabriele et al., 2004).



**Fig. 7.** Schematic setup for LIBS based sorting technique. Nd: YAG laser pulses induce plasma at waste pieces on the conveyor belt. Plasma radiation is detected in backward direction using fiber optics and grating spectrometer with a CCD detector and fast read-out electronics.

A LIBS system is composed of a solid state (Nd: YAG) Neodymium-doped yttrium aluminum garnet laser, a CCD spectral range spectrometer and a processing unit for fast data analysis (see Fig. 7). First, the bulk waste is brought into the inspection area, where the laser is focused over it. This leads to ablation of waste material, which generates plasma plumes (see Fig. 7). The radiation emitted from the ablated portion is captured by the CCD spectrometer. The optical spectroscopy reads and distinguishes the characteristic atomic emission lines and enables a quick analysis of the bulk waste followed by the detection of constituent materials. Next the mechanical system sorts the detected constituent materials into their respective bins.

An advantage of LIBS is that the segregation of waste takes place at a relatively higher volume and speed compared to the eddy current technique. A limitation of LIBS is that the waste sample must be free from lubricants, paints, or oxide layers (Gesing and Harbeck, 2008). In practice, this may be difficult to ensure.

**Metal:** Grzegorzek et al. (2011) developed a system in which a LIBS system is mounted over the conveyor system for acquiring material data. It had a camera and a line laser for sensing metals. Machine learning algorithms such as Naive Bayes (NB), support vector machines (SVM), and nearest-neighbor (NN) were used to classify materials based on their characteristic spectral emission signatures. SVM reportedly provided an accuracy of about 71% (Grzegorzek et al., 2011). A multivariate analysis technique is also used to estimate the elemental composition of test material and to classify (Gurell et al., 2012a, b).

**Plastic:** The recovery of plastic waste can also be performed by LIBS. When applied to plastics, it is sometimes called LIPS (Laser Induced Plasma Spectroscopy) instead (Sattler, 1990; Sattler and Yoshida, 1993). Gondal et al. (2007) proposed a LIBS based system which can identify various plastics like High Density Polyethylene (HDPE), Low Density Polyethylene (LDPE), Polypropylenes (PP), Polystyrene (PS), Poly(ethylene terephthalate) (PET) and Poly(vinyl chloride) (PVC) on the basis of their carbon and hydrogen (C/H) line intensity ratio. Anzano et al. (2006) and Gornushkin et al. (2000) proposed a compact and reliable method for instant classification of different types of plastic particles by utilizing statistical analysis such as linear and rank correlations with LIPS. The spectra from the plastics are collected and monitored in the 200–800nm spectral window and compared with reference libraries. These libraries are built using the spectral data from different groups of recycled plastic samples. Anzano et al. (2008) developed a system which overcomes the limitations in the previous method (Anzano et al., 2006), wherein the laser radiation atomizes the molecular particles of plastic when exposed. The classification is performed by utilizing instant ratio analysis of molecular bands for identification of different energetic materials (Anzano et al., 2008).

**Wood:** The wood waste quality is categorized into three types, namely, (i) ‘A’ type untreated wood such as wooden pellets, (ii) ‘B’ type painted or glued wood with nails such as frames, doors, and chipboards, and (iii) ‘C’ type treated with hazardous wood preservatives such as construction and demolition (C&D) wood waste. Isolating treated wood waste from untreated wood waste is a major concern, as it can contaminate the untreated wood waste. Treated C type wood waste hosts a lot of preservatives like oil-borne preservatives, organic solvents and chromate copper arsenate (CCA) (Jacobi et al., 2007; Solo-Gabriele et al., 2004).

Several techniques have been proposed to sort CCA treated wood from the other wood waste types (Aono et al., 2012; Fellin et al., 2014; Hasan et al., 2011a,b; Jacobi et al., 2007; Solo-Gabriele et al., 2004). Aono et al. (2012) proposed the identification of CCA-treated wood by using a laser to form and analyze the plasma. Uhl et al. (2001) reported analysis of treated wood by LIBS and concluded that LIBS has the capacity to distinguish heavy metals in wood.

The LIBS technique utilizes an Nd: YAG laser emitter as seen in Fig. 7. The pulse emitted from the laser is focused onto the wood to produce a plasma of excited atoms. The plasma

fluorescence is then passed via optical fiber to a CCD spectrometer. Later, these spectra are classified by comparing them against the reference fluorescence intensities (Aono et al., 2012; Solo-Gabriele et al., 2004). The distance between the specimen and the LIBS detector is on the order of a few feet. Thus, a detection window of about 8cm is estimated for LIBS system, which simplifies the conveyor system design for feeding the sample to the detector (Solo-Gabriele et al., 2004). A summary of typical LIBS based sorting techniques is presented in Table 2.

**Table 2**

A summary of typical LIBS technique applied for the recovering different materials from mixed waste

<b>Techniques</b>	LIPS/LIBS based method
<b>Types of materials recovered</b>	Aluminum alloys (Cast and Wrought), HDPE, LDPE, PS, PP, PET, PVC, CCA treated wood
<b>Types of sensors</b>	Nd: YAG laser, CCD spectrometer, CMOS spectrometer
<b>Main process features</b>	Detects composition of elements in materials based upon spectral analysis
<b>Classification success &amp; recovery rate (in %)</b>	80-97
<b>Limitations</b>	<ul style="list-style-type: none"> <li>• Significant fluctuation in signal intensity is possible, which can cause uneven energy distribution between material composition and laser pulse due to varied plasma generation.</li> <li>• The excitation of pulse is limited to small region for elemental analysis.</li> <li>• Sensitive to surface contamination.</li> </ul>
<b>Reference</b>	Anzano et al., 2006, 2008; Aono et al., 2012; Fellin et al., 2014; Gesing and Harbeck, 2008; Gondal et al., 2007; Gornushkin et al., 2000; Grzegorzec et al., 2011; Gurell et al., 2012a,b; Hark and Harmon, 2014; Hasan et al., 2011a,b; Jacobi et al., 2007; Solo-Gabriele et al., 2004

### 2.3.3. X-ray based sorting

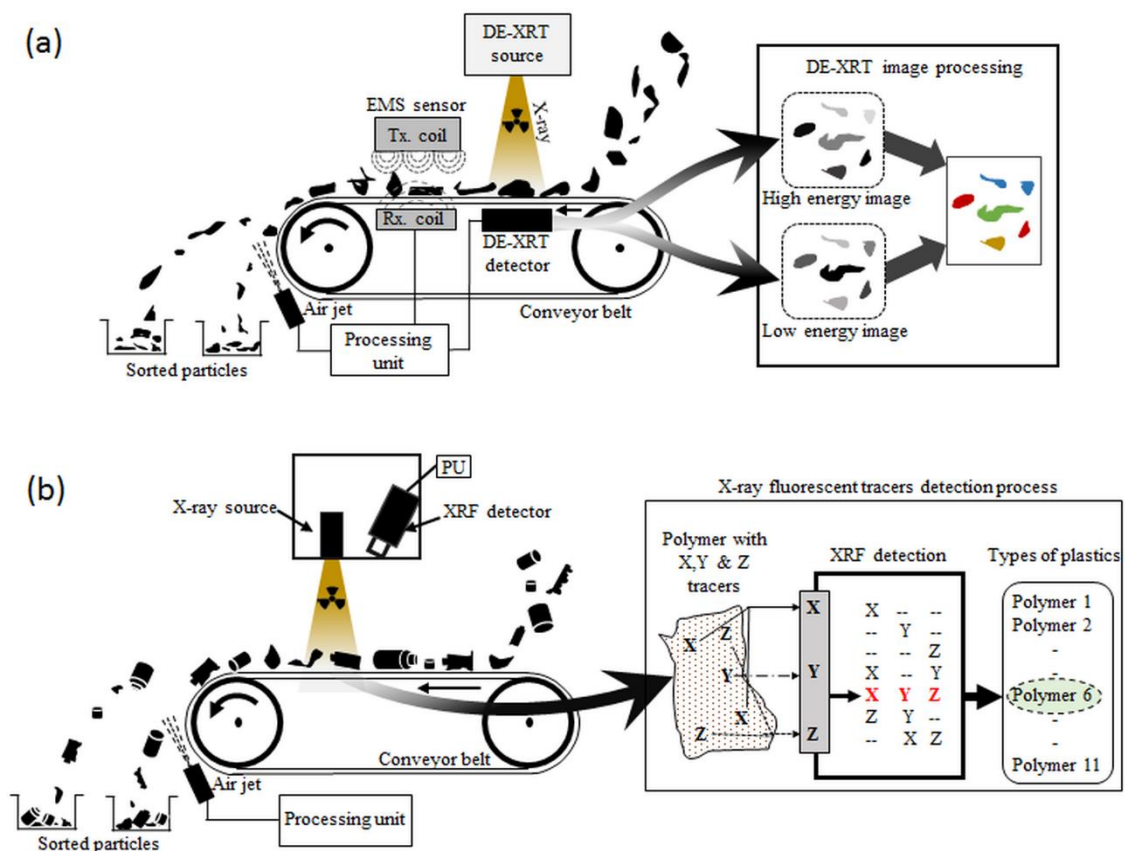
X-ray transmission (XRT) is an indirect sorting technique (de Jong and Dalmijn, 2002; De Jong et al., 2003; Mesina et al., 2007). X-ray transmission based sorting is relatively fast, capturing X-ray images within a few milliseconds. An imaging module utilizes a high-intensity X-ray beam. When X-rays penetrate into the material, some of its energy gets absorbed by the material, while the rest is transmitted through to a detector at the bottom (shown in Fig. 8). The detected radiation can be analyzed to provide information about the atomic density of the material. X-ray sorting can be categorized into two types: Dual Energy X-ray Transmission (DE-XRT) and X-ray Fluorescence (XRF).

**Metal:** In the recovery of metals, X-ray beam absorption depends upon the density and the thickness of the target metal fraction (Mesina et al., 2007; Rao, 2006b). The DE-XRT is a modified version of the X-ray transmission technique, wherein a dual-emission X-ray is applied to materials with different energy levels, i.e., two beams of different wavelengths (Bokun and Osadchii, 2010; Mesina et al., 2007). The attenuation of X-ray radiation is more in a higher density material medium compared to a lower density material medium. The identification of various waste fractions is performed by determining density difference (see Fig. 8(a)) using Lambert's Law (Von Ketelhodt and Bergmann, 2010).

Using a combination of different sensors (hybrid/multi-sensor combination) can improve the characterization and sorting accuracy of metal wastes (Koyanaka and Kobayashi, 2010; Mesina et al., 2007; Rahman and Bakker, 2012; Takezawa et al., 2015). The combination of DE-XRT and EMS (see Fig. 8(a)) is observed to have better efficiency and classification of material (Mesina et al., 2003; Rahman and Bakker, 2012), as compared to other standalone systems. Reportedly it is difficult to distinguish wrought and cast aluminum (Mesina et al., 2003, 2007; Takezawa et al., 2015). This problem can be solved using hybrid technology for better efficiency.

**Plastic:** Recovery of plastic waste fractions can be performed using XRF techniques. This technique is only applicable in recovering PVC from PET, PP, etc., (Brunner et al., 2015). The principle behind XRF technique is that the individual atoms are excited by an external laser source leading to emission of X-ray photons. The emitted photons create a unique spectral signature corresponding to the atomic weight/element type. In case of a compound like plastic the corresponding spectral signature is a superposition of the spectral signatures of the constituent elements which can be identified using machine learning techniques.

Bezati et al. (2010a, 2011a) proposed a new approach, EDXRF (Energy Dispersive X-ray Fluorescence) for sorting plastic particles based upon tracers added to the polymer matrix, which increases the sorting selectivity of polypropylene. The tracers are formed by many substances which are dispersed into the material (Bezati et al., 2010b, 2011b). Fig. 8(b) shows a schematic representation of this technique. X-ray beam is focused and passed through the small portion of



**Fig. 8.** (a) DE-XRT and EMS based sorting technique utilizes the property of electrical conductivity and density for classification and compressed air jet for segregation. (b) EDXRF based sorting technique.

the material, and it travels to the detector. The signal from the detector is then passed to the processing unit, which controls the X-ray source. The XRF spectral signal is analyzed and utilized for the separation of materials containing specific amounts of tracers (Bezati et al., 2010a,b, 2011a,b; Brunner et al., 2015). XRF is a non-destructive elemental analysis and is capable of identifying black polymers and surface contaminated fractions with X-ray penetration of up to 1mm depth (Bezati et al., 2011a).

**Wood:** The X-ray fluorescence (XRF) system can effectively identify arsenic in wood waste (Hasan et al., 2011b; Moskal and Hahn, 2002; Solo-Gabriele et al., 2004). When X-ray beams are projected onto a wooden sample, a fluorescence is generated due to the relaxation of the atoms. The fluorescence released depends upon the tracers of various elements present in the wooden specimen (shown in Fig. 8(b)). Research has shown that the presence of copper, arsenic and chromium can be identified using the XRF technique (Blassino et al., 2002; Fellin et al., 2014; Hasan et al., 2011a,b; Solo-Gabriele et al., 2004).

The XRF system is composed of an X-ray tube and a solid state detector. The XRF system is mounted approximately 1 foot above the wood specimen. The X-ray tube and detector are fitted in a closed chamber, and a software driven digital pulse processor is connected to the detector (Blassino et al., 2002; Solo-Gabriele et al., 2004). The classification/identification of metals such as As, Cr, and Cu depends upon the reflection of concentrated metals in the wooden waste fragments and is detected by the XRF detector. The recovery efficiency achieved is 98%, 97% and 91% for As, Cr, and Cu respectively (Hasan et al., 2011a, b). A summary of typical X-ray based sorting techniques is presented in Table 3.

**Table 3**

A summary of typical X-ray based sorting techniques applied for recovering different materials from mixed waste

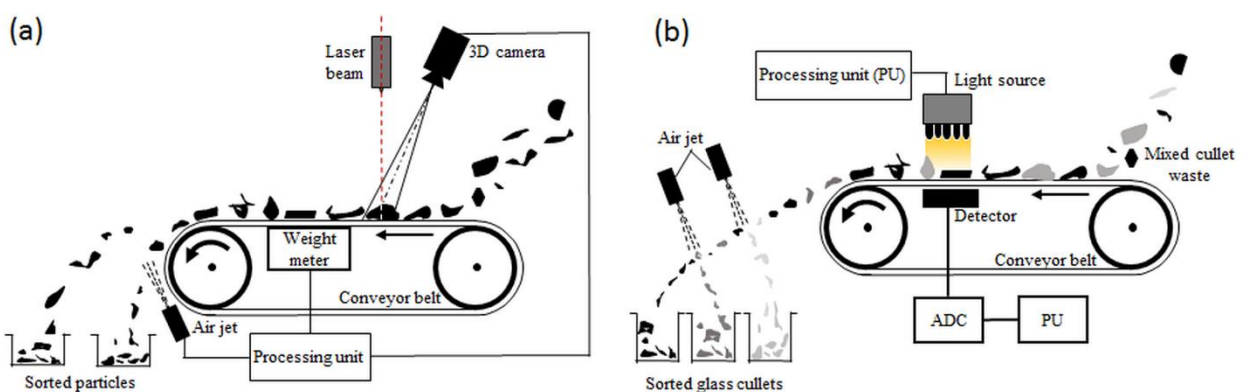
Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	Reference
XRT/DEXRT and EMS method	Cast and wrought aluminium, Cu, Mg	Line scan camera, DE-XRT detector, EMS	Specific atomic density of material irrespective of size, moisture or dust is detected	90-97	<ul style="list-style-type: none"> <li>Issue in categorizing wrought and cast aluminum (can be overcome by hybrid techniques).</li> <li>DEXRT inefficient for smaller particles.</li> </ul>	Bergmann, 2010; Mesina et al., 2007; Von Ketelhodt and Bergmann, 2010; Takezawa et al., 2015
XRF based	PVC	X-ray source, XRF detector	Detects elemental composition of material in the form of tracers based upon atomic density	92-96	<ul style="list-style-type: none"> <li>XRF cannot differentiate plastic types (except PVC).</li> </ul>	Bezati et al., 2010a,b; 2011a,b
XRF based	As, Cr, Cu treated wood	X-ray tube, solid state detector	Detect reflectance of particle signature of the material	91-98	<ul style="list-style-type: none"> <li>Identification of tracers are limited to periodic table.</li> </ul>	Blassino et al., 2002; Hasan et al., 2011a,b; Solo-Gabriele et al., 2004

### 2.3.4. Optical based sorting

Traditional techniques often relied on physical properties (Mesina et al., 2003; Rao, 2006a; Rahman and Bakker, 2012; Tam, 2008) but ignored visual/tactile cues like color, shapes, texture and size for the sorting of waste. In optical sorting, camera based sensors are used for the identification of waste fractions. The following sections present some commonly used optical sorting techniques.

**Metal:** A hybrid system with a combination of color vision and an inductive sensor array can identify metals such as copper, brass, zinc, aluminum, and stainless steel (Kutilla et al., 2005). Regions with a larger red component in an image of mixed metals indicate copper and brass, while regions of blue indicate stainless steel and aluminum. The inductive sensor measures the electrical property of metal scraps using an array of 52 inductive sensors (Kutilla et al., 2005). The identification of material is based upon color differences and electrical conductivity. The hybrid technique can eliminate the limitations of other non-hybrid techniques due to surface contamination (Kutilla et al., 2005).

An optical sorting technique using multivariate analysis includes a combination of a 3D shape detection camera and a weight-meter, fixed along the conveyor system (shown in Fig. 9(a)) (Koyanaka and Kobayashi, 2010, 2011). A large number of non-ferrous (NF) metals like magnesium, wrought aluminum, and cast aluminum are recovered in this technique with a sorting efficiency of 85% (Koyanaka and Kobayashi, 2010, 2011). The accuracy of this method is not affected by surface contaminants like paint, oil, and dust. In addition, the technique can also sort highly irregular material shapes. Installation and running cost is relatively less compared to other techniques like XRT or LIBS. The modification in multivariate data makes it possible for re-learning the neural network for obtaining higher sorting accuracy (Koyanaka and Kobayashi, 2011).



**Fig. 9.** (a) Optical sorting technique consisting of a 3D imaging camera, weight meter, belt conveyor and an air compressor. The 3D camera is equipped with a linear laser and optical CCD (determines the height of each fragment). A compressed air jet is used for ejecting various fractions. (b) Color sorting technique of ceramic glass contaminants composed of a light source and sensor. The sensor detects the glass cullets and generates an analog signal corresponding to the amplitude of light passed through the sample. The analog signal is converted to digital using ADC followed by determination of respective fractions and ejection into respective bins

Huang et al. (2010) proposed a sorting technique based on features like shape and color. This technique combines a 3D color area scan camera with a laser beam attached to the conveyor belt (see Fig. 9(a)). This technique is known as triangulation scanning, wherein a triangle is formed among the laser beam, the camera, and the laser emitter (Huang et al., 2010). The technique claims an accuracy of about 98% for NF metals and 99% for plastic fractions.

**Glass:** Recovery of glass fractions (cullets) can be performed using optical sorting techniques via color based classification, as glass cullets typically have pieces with various colors like red, blue, green or any combinations thereof (Afsari, 2008; Afsari and Dimsdale, 2008; Doak, 2000). In this method, the sensor scans and measures the attenuation of light of various colors which pass through the sensing region.

Fig. 9(b) illustrates a schematic representation of the color sorting technique. The figure shows that at first the unsorted glass cullets are passed through the inspection zone, where LEDs successively emit lights of red, blue and green wavelengths. Depending upon the color of the specimen, the light emitted from the LEDs undergoes attenuation (Afsari and Dimsdale, 2008; Doak, 2000). These attenuated color components are then compared against known reference colors and thereby the color of the specimen is identified. Identified cullets are then sorted into particular bins using a compressed air jet (see Section 2.2.(m)). One of the drawbacks of this technique is that it may misclassify glass samples with paper/plastic labels. This can be overcome by using infrared and ultraviolet wavelengths instead of visible wavelengths. Infrared and UV penetrate through paper labels and can help in the identification of a sample with paper labels.

The ultraviolet (UV) sorting technique is used to distinguish opaque and other special glasses (ceramic glass, lead glass, borosilicate glass, etc.) from mixed glass scrap (Huber and Leitner, 2014; Huber and Pansinger, 2011). The technique is entirely independent of the color and the shape of the glass specimen. Detection is performed by radiating UV light over the glass specimen. Based on the properties of the glass specimen, UV is absorbed and attenuated. The intensity of the attenuated UV is then compared with a standardized reference value and thereby the specimen is classified. The classified glass specimen is then diverted to a predetermined bin location with air jet nozzles as described in Section 2.2.(m) (Huber and Leitner, 2014; Huber and Pansinger, 2011).

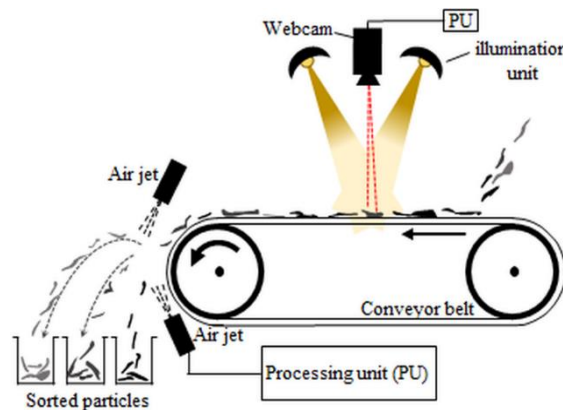
**Paper:** Use of optical sorting of various types of papers from waste has been reviewed in detail elsewhere (Rahman et al., 2014). Rahman et al. (2009) performed sorting of various types of papers like old corrugated cardboard (OCC), old news paper (ONP) and white paper (WP) using image processing methods. The technique transforms an image of a paper waste stream to a quantized image. Then the co-occurrence matrix is calculated from the quantized image (Pham and Alcock, 2002). Later, the paper grades are identified and segregated into their respective bins using a rule-based classifier (see Fig. 10) (Rahman et al., 2009).

Template matching techniques transform pixel values of a captured image to a red-green-blue (RGB) value. To identify different paper grades, the transformed RGB strings are compared with the template images by searching in an N-cell (Rahman et al., 2009). Rahman et al., 2012a explored DNA computing based on a template matching technique for the classification of

recyclable paper. DNA computing methods have also been explored by other researchers (Rahman et al., 2012a, Watada and binti Abu Bakar, 2008; Yeh and Chu, 2008).

Rahman et al. (2011) performed identification of paper grades (WP, ONP, and OCC) using the KNN classifier technique. To train the classifier, feature vectors were obtained from ten samples of each paper grade. Paper grades were then identified using the trained KNN classifier and a success rate of 93% has been reported.

A smart vision sensing (SVS) system was proposed that can identify various paper grades, namely, WP, ONP, and OCC using case-based reasoning (CBR) with window features (Rahman et al., 2010). The technique is based upon the maximum occurrence of a particular reference template in the paper image. Matching scores of reference image templates are determined, which then help in identification of respective paper grades (Rahman et al., 2010).



**Fig. 10.** The optical sorting technique consists of web-camera, conveyor belt, and air compressor. Web-camera sensor can segregate different paper grades using texture information.

Another SVS system has been proposed based upon the conversion of RGB pixels of the captured image into the HSI (hue, saturation, and intensity) color scale (Rahman et al., 2010, 2012a). In this approach brightness and intensity information is ignored, overcoming the need for consistent illumination during the identification phase. An accuracy of 90% was reported using this approach (Rahman et al., 2010, 2012a). A summary of typical optical sorting techniques is presented in Table 4.

**Table 4**

A summary of typical optical based sorting techniques for recovering of different materials from mixed waste

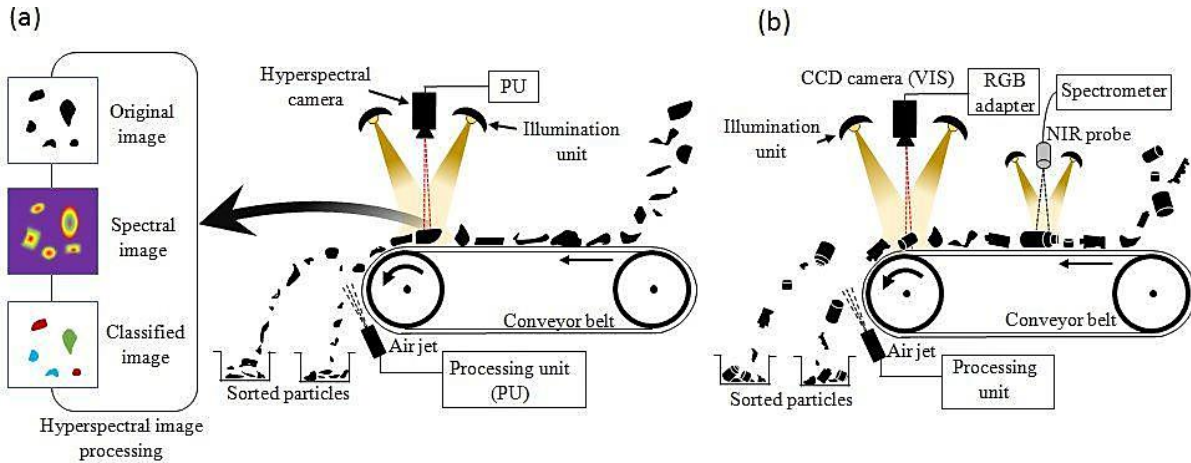
Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	Reference
Optical sorting method	Cu, Al, Mg, Zn, SS, Ni, Br	3D imaging camera, Optical CCD, Linear laser	Material color (red, green, and blue), shape and size properties detected	86-95	<ul style="list-style-type: none"> <li>Inductive sensors are sensitive to distance changes.</li> <li>Complex shapes of material can cause variation in measurement.</li> </ul>	Huang et al., 2010; Koyanaka and Kobayashi, 2010, 2011; Kutila et al., 2005
Co-occurrence feature sorting	WP, ONP, OCC	Web camera (Logitech Quickcam Pro 4000)	Classification is done through rule-based classifiers and by energy for the co-occurrence matrices	90.67	<ul style="list-style-type: none"> <li>Unsuitable for real-time implementation.</li> <li>High computational</li> </ul>	Pham and Alcock, 2002; Rahman et al., 2009

					time.	
Template matching/ DNA computing algorithm	WP, ONP, OCC	Web camera	RGB string is applied over entire pixels and template matching is done.	90-96	<ul style="list-style-type: none"> <li>• Varied illumination can cause error in detection.</li> <li>• High computational time.</li> </ul>	Osiur Rahman et al., 2009; Rahman et al., 2012a; Watada and binti Abu Bakar, 2008
Dominant color	WP, ONP, OCC	Web camera	Features taken: Histogram scale length on the dark side, histogram scale length on the light side, energy, mode using KNN classifier and by absolute distance metric	93	<ul style="list-style-type: none"> <li>• Performance is influenced by lighting conditions.</li> <li>• Consistent illumination is required.</li> </ul>	Rahman et al., 2011
Windows feature method with RGB color space	WP, ONP, OCC	Web camera	RGB component mode and energy taken by CBR approach: case base reasoning	95.17	---	Rahman et al., 2012b
Windows feature with HSI color space	WP, ONP, OCC	Web camera	Mean of hue and mean of saturation are calculated by chromaticity: with window-based subdivision, distance, and voting	91.07	<ul style="list-style-type: none"> <li>• Weight of the throughput depends upon the grade and size of the paper.</li> </ul>	Rahman et al., 2010, 2012a
Optical sorting	colored glass (red, green, blue)	Line scan camera	Properties based upon their color intensities	---	<ul style="list-style-type: none"> <li>• Possibility of misreading of colors due to film buildup,</li> <li>• Cullet furlowing can cause non-uniformities.</li> </ul>	Afsari, 2008; Afsari and Dimsdale, 2008; Doak, 2000
Ultraviolet based sorting	ceramic glass, lead glass, borosilicate glass	Ultraviolet sensor	Material is identified based on monochromatic properties	---	<ul style="list-style-type: none"> <li>• Detection of non-transparent or low-transparent impurities are not possible.</li> </ul>	Huber and Leitner, 2014; Huber and Pansinger, 2011

### 2.3.5. Spectral imaging based sorting

Spectral imaging combines both spectral reflectance measurement and image processing technologies (Picon et al., 2009, 2010; Tatzer et al., 2005). Various reported spectral imaging based techniques include NIR (near infrared), VIS (visual image spectroscopy) and HSI (hyperspectral imaging) (Bonifazi and Serranti, 2006; Jansen et al., 2012; Kreindl, 2011; Serranti et al., 2006; Vegas et al., 2015).

A hyperspectral imager is similar to a laboratory spectrometer, which produces images over a continuous range of narrow spectral bands and facilitates the spectroscopic analysis of data. A schematic representation of hyperspectral sorting is shown in Fig. 11(a). The conveyor system transports the waste fractions underneath the monitoring station, and the spectral CCD camera acquires spectral data continuously at a fixed frequency. After data pre-processing and reduction, a classification algorithm is applied to the spectral data to perform material classification (Picon et al., 2009; Picon et al., 2012; Tatzer et al., 2005). An array of compressed air nozzles is mounted at the end of the conveyor belt and depending upon the material (see Section 2.2.(m)), individual nozzles are triggered to segregate waste fractions into their respective bins (see Fig. 11(a)) (Tatzer et al., 2005).



**Fig. 11.** (a) The hyperspectral sorting technique consists of a spectral CCD camera that identifies the particles based upon their spectral signature and segregates waste fractions into their respective bins using compressed air nozzles. (b) Spectroscopic sorting technique consists of a CCD camera and NIR spectrometer.

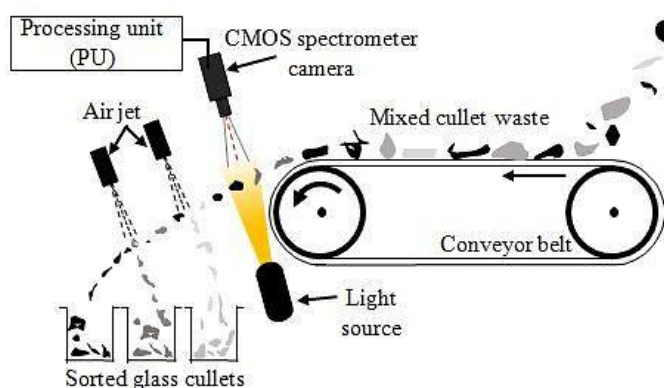
**Metal:** Picon et al. (2009) reported a classification algorithm based upon spatial and spectral feature integration in conjunction with a custom designed hyperspectral data and decorrelation scheme for the recovery of metal waste fractions (Picon et al., 2009, 2010). The FUSSER (Fuzzy Spectral and Spatial classifiER) algorithm was developed for the sorting of non-ferrous materials like aluminum, white copper, stainless steel, brass, copper, and lead, and is reported to have a classification rate of 98%. A limitation of the approach is that it fails to distinguish stainless steel if it has the same spectral information as other non-ferrous metals (Picon et al., 2009).

**Plastic:** In spectroscopy based techniques, light is illuminated on a plastic waste sample. Due to the interaction between light and the sample, a unique set of wavelengths of light gets reflected for each type of plastic present in the sample. Various sensors like NIR, MIR, and laser Raman are used for reading the signature of reflected wavelengths from the target material. Later, the material to be sorted out is determined by the processor unit.

Safavi et al. (2010) developed a technique by utilizing VIS reflectance spectroscopy to identify PP plastic in mixed waste. The setup consists of a material handling system and a detection unit (see Fig. 11(b)); the conveyor system is used to transport the mixed waste to the detection unit where a VIS light source illuminates the sample. The identification unit utilizes VIS spectrometer to analyze the reflected light from the sample and determine the materials present in the sample. The compressed air nozzle ejects the particles into their respective bins as described in Section 2.2.(m) (Safavi et al., 2010).

The HSI based approach aims in classifying polyolefin particles from mixed waste by recovering PP and PE plastics with high purity in the NIR range (1000–1700nm) (Serranti et al., 2010, 2011, 2012). Fig. 11(b) illustrates a typical spectroscopy system, wherein the HSI system is equipped with a moving conveyor belt and sensing system comprising an illumination and NIR spectral camera. First, materials are brought under the inspection zone via the conveyor. After this, the NIR camera captures an image of the sample. The image is then processed using a classification algorithm.

Various approaches for improving the performance of the classification algorithm have been reported. It has been reported the use of principal component analysis (PCA) to reduce the dimensionality for classification of the spectral data obtained from the NIR image (Serranti et al., 2011, 2012). Kassouf et al. (2014) developed a fast way of classifying plastics like PET, PE, PP, PS and polylactide (PLA) by a combination of MIR spectroscopy along with independent component analysis (ICA). In addition to this, a more accurate classification was obtained by separating plastic waste belonging to a specific family of polymer e.g., LDPE and HDPE. Due to the high penetration depth of NIR radiation, pre-treatment of a sample is not required and the speed of measurement is often high. However, the technique cannot detect black polymer materials effectively due to their high absorptivity.



**Fig. 12.** On-line sorting of ceramic glass contaminants, which consists of a CMOS spectrometer camera, conveyor system and ejection system. The cullets are passed through a detection system and analyzed by their characteristic feature (usually shapes, thickness, and color) and ejected into respective bins using a compressed air jet.

**Glass:** Serranti et al. (2006) proposed an approach to recognize ceramic glass using spectral signatures in the MIR range. The spectral characterization of glass and ceramic glass fractions were performed and the specific wavelength ratio of two classes of materials can be recognized using the spectral signature (Serranti et al., 2006). Bonifazi and Serranti (2006) proposed an approach for identifying and sorting between useful (glass) and pollutant (ceramic glass) materials as shown in Fig. 12. This approach utilizes the VIS and NIR spectrum, by comparing the detected materials with reference samples of glass and ceramic glass representing different shapes, thicknesses and colors.

Hyperspectral imaging based sensing devices are often installed for on-line recognition of glass and ceramic glass fractions inside glass recycling plants (Bonifazi and Serranti, 2006). NIR is applied in statistical classifiers for recognizing the spectral signatures of materials. A summary of typical spectral imaging based sorting techniques is presented in Table 5.

**Table 5** A summary of typical spectral based sorting techniques applied for recovering of different materials.

Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	Reference
Hyperspectral based sorting	Cu, Al, Pb, SS, Brass	Spectral CCD camera	Detects spectral signature and color properties of material.	95-98	•HSI fails to discriminate stainless steel if it has the same spectral information with other non-ferrous metals.	Picon et al., 2009; 2010, 2011, 2012;Tatzer et al., 2005
Spectroscopy analysis method	PE, PET, PP, PS, PLA, LDPE, HDPE	NIR, MIR, VIS spectrometers	Material color (red, green and blue) and spectral signature are detected.	96-98		Kassouf et al., 2014; Safavi et al., 2010; Serranti et al., 2010, 2011, 2012
Spectral sorting approach	Ceramic glass	CMOS spectrometer camera (NIR, VIS, HSI)	Detects spectral signature of the material.	---	•VIS signal ignores material with label and surface contaminants.	Bonifazi and Serranti, 2006; Serranti et al., 2006

### 3. Discussion

In the last 50 years, a wide variety of segregation/separation technologies such as size separation, EMS/magnetic field separation, and sensor based separation have been developed for MSW sorting. Size separation/reduction plays a vital role in pre-processing before the sorting process. Incorporation of automation techniques in MSW sorting has improved the efficiency of sorting systems in addition to the quality, consistency and safety of the recycling process (Parasuraman et al., 2000; Satchell, 1998). Based upon the level at which automation is applied, the automated sorting techniques for recycling can be broadly grouped into three levels, namely, (i) device level, (ii) machine level, and (iii) system level.

**Device level:** This is the lowest level, which includes actuators, sensors and other devices connected into an open loop system, which are connected into individual control loop of the machine in automated sorting system. Actuators include prime movers like, motors to drive the material handling system. Typically, sensors include eddy current and magnetic sort (Al-Salem et al., 2009; Hansen et al., 2007; Jank et al., 2015; Krivtsova et al., 2009; Svoboda, 2004; Yuan et al., 2015).

**Machine level:** In this level, the device level components are assembled in an individual machine and are configured in a closed loop (Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012).

**System level:** In this level, the group of machines or workstations are interconnected or supported by material handling systems, computer and other peripheral equipment. The operations performed at this level are under centralized instructions. Various machines like comminution, inspection, material handling and separation systems are coordinated for an efficient automated material handling, detection and binning (Anzano et al., 2006, 2008; Bergmann, 2010; Grzegorzec et al., 2011; Hasan et al., 2011a,b).

Fig. 13 illustrates the year-wise variation of the number of publications in the area of automated sorting for recycling from MSW during 2004–2015, taking into account both journal and conference publications. We have plotted the number of publications in the area of device level, machine level, and system level separately in Fig. 13 and from this we can observe that:

- the number of publications in the area of system level is more than the other two levels,
- there is a sharp peak in research activity in the area of system level automation between 2010–2011,
- the research activities in device and machine level automation has been regular, and
- there is a growing interest among researchers to move device and machine level approaches to fully automated systems.

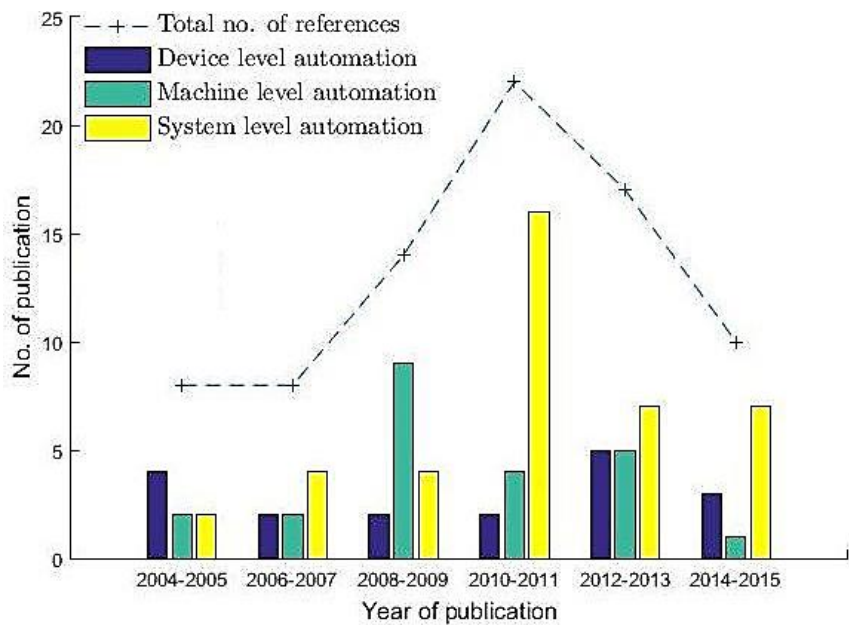


Fig. 13. Number of publications versus year of publication.

We have discussed in detail the design aspects of various automated sorting technologies for recycling from MSW. The characteristics of sorting techniques are material diversity, accuracy, performance, robustness, flexibility, and reliability. Table 6 presents a summary of the characteristics of various sorting techniques.

Table 6 Overall performance of sensing technologies

Various Technologies	Material diversity	Accuracy	Performance	Robustness	Flexibility	Reliability
Eddy current	L	M	L	H	L	H
LIBS	M	H	H	M	M	H
X-ray based	M	H	M	H	M	H
Optical based	H	M	H	L	M	M
Spectral based	H	H	H	M	M	H

L: Low, M: Medium, H: High

LEGENDS: Material diversity: L: < 8, M: 8-12, H: > 12, Accuracy: L: < 90%, M: 90 – 96%, H: > 96%, Fast: L: > 1.5m/s, M: 1.5 – 0.5m/s, H: < 0.5m/s

Material diversity is measured in terms of the number of different recyclable materials that a particular technique can recover. Eddy current techniques sort only metals, which results in low material diversity. The accuracy of solid waste identification is a vital characteristic to determine the utility of a sorting technique. The computational performance of a system is another very important characteristic. In the case of real-time sorting, the classification algorithms need to be computationally fast for improved efficiency. The environment of a waste sorting system consists of many factors that may be uncertain and noisy. The system must provide a robust decision in rough environments; for instance, the system must be insensitive to variable illumination, vibrations, and dust. The system must be flexible to the user, and the users must be able to change the settings of the system as required. For reliability, the system should detect its failure automatically and then raise an alarm with necessary corrective suggestions.

We have observed that for segregating metal waste fraction, eddy current technique is most commonly utilized. Metal waste fraction is also sorted using other methods with the advent of optical, x-ray and spectral imaging based techniques. The optical and spectral based techniques have better performance with greater coverage of material varieties.

Based on the level of development, we classify the reported automated waste sorting systems into four categories, namely, research level, laboratory prototype, pilot scale, and full-scale shown in Table 7. Research level systems are proof of concept type and the developed system is not tested extensively. Laboratory prototypes are reduced systems which are tested for a limited number of test scenarios designed in a laboratory. Pilot scale systems are those that are tested for a limited number of test cases in the production environment. In full-scale systems, extensive testing is performed in real production environment.

**Table 7**  
Summary of complete automated sorting of recyclables with its work status.

Status	Types of System	References
Research	Direct sorting	Fraunholz, 2004; Kasper et al., 2015; Kelland et al., 1974; Lowell and Rose-Innes, 1980; Oberteuffer, 1973; Patachia et al., 2011; Rem et al., 1998; Richard et al., 2011; Svoboda, 2004; Takoungsakdakun and Pongstabodee, 2006; Wang et al., 2015; Wu et al., 2013
	Indirect sorting	Al-Salem et al., 2009; Bonifazi and Serranti, 2012; Braam et al, 1988; Gaustad et al., 2012; Gesing and Harbeck, 2008; Gornushkin et al., 2000; Osiur Rahman et al., 2009; Pham and Alcock, 2002; Rahman et al., 2009; Safavi et al., 2010; Sattler, 1990; Sattler and Yoshida, 1993; SchlÄumann, 1975; Von Ketelhodt and Bergmann, 2010; Watada and binti Abu Bakar, 2008
Laboratory scale	Direct sorting	Bakker et al., 2009; Cazacliu et al., 2014; de Jong and Dalmijn, 1997; Hu, 2014; Jank et al., 2015; Krivtsova et al., 2009; Li et al., 2007; Li et al., 2015; Pita and Castilho, 2016; Wang et al., 2012; Wang et al., 2014; Yuan et al., 2015
	Indirect sorting	Afsari, 2008; Anzano et al., 2006; Anzano et al., 2008; Aono et al., 2012; Bezati et al., 2010a,b, 2011a,b; Brojboiu et al., 2013; Fellin et al., 2014; Gondal et al., 2007; Gurell et al., 2012a, b; Huang et al., 2010; Huber and Pansinger, 2011; Jacobi et al., 2007; Kassouf et al., 2014; Koyanaka and Kobayashi, 2010; Koyanaka and Kobayashi, 2011; Mesina et al., 2003, 2007; Picon et al., 2009, 2010, 2011, 2012; Rahman and Bakker, 2012; Rahman et al., 2010, 2011, 2012a,b; Serranti et al., 2006, 2010, 2011, 2012; Solo-Gabriele et al., 2004; Takezawa et al., 2015; Uhl et al., 2001
	Direct sorting	Hansen et al., 2007; Holloway , 1989; Luciani et al., 2015; Muchova et al., 2009; Rem et al., 2012; Vajna et al., 2010

Pilot scale	Indirect sorting	<a href="#">Afsari and Dimsdale, 2008</a> ; <a href="#">Blassino et al., 2002</a> ; <a href="#">Buchan and Yarar, 1995</a> ; <a href="#">Doak, 2000</a> ; <a href="#">Huber and Leitner, 2014</a> ; <a href="#">Mesina et al., 2003</a> ; <a href="#">Noll et al., 2001, 2008</a> ; <a href="#">Tatzer et al., 2005</a>
Full scale	Direct sorting	<a href="#">Holloway, 1989</a> ; <a href="#">Ohara et al., 2001</a> ; <a href="#">Roman, 1992</a> ; <a href="#">Svoboda and Fujita, 2003</a>
	Indirect sorting	<a href="#">Bonifazi and Serranti, 2006</a> ; <a href="#">Grzegorzec et al., 2011</a> ; <a href="#">Hasan et al., 2011a,b</a> ; <a href="#">Kujala et al., 2015</a> ; <a href="#">Kutilla et al., 2005</a> ; <a href="#">Lukka et al., 2014</a>

#### 4. Conclusions

This paper presents a state of the art review in the area of automated sorting techniques and systems for the purpose of recycling MSW. Various elements of industrial level automation systems including material handling, imaging (NIR, MIR, VIS, X-ray, etc.), and a vast array of direct sorting techniques (magnetic, eddy current, etc.) are surveyed in this paper. In particular, this paper highlights schematics of prevalent waste sorting techniques, sensors, material handling systems and levels of automation incorporated in systems reported during 2004–2015.

We observe that most of the research advances in the area of automated waste sorting systems have taken place in developed countries. In developed countries, source segregation of waste into recyclables is very common. Therefore most of the automated waste sorting systems have been designed and are suitable only for the automated sorting of source-segregated waste. In contrast to this, source segregation is usually not implemented in developing countries due to very limited door-to-door collection and lack of motivation. As a result, the collected waste is in mixed form and is later dumped in landfill sites. After this, waste sorting is performed manually and exposes involved workers to toxic and pathogenic work environment. Therefore, a need exists to facilitate the workers involved in mixed waste sorting with automated tools to improve safety and efficiency ([Paulraj et al., 2016](#); [Takemura et al., 2006](#)).

This opens up a research problem to develop automated systems for handling mixed waste. It must be kept in mind that the cost of automated waste sorting technology will play a significant role in its acceptability in the developing countries. Therefore, it is imperative to develop low cost and pervasive automated waste sorting technologies for solving the problem of waste management in the developing countries. The following technical challenges need to be tackled in order to achieve automated handling of MSW:

- (i) *Multi-sensor fusion*: Due to the mixed nature of the waste the automated recovery of recyclables is very challenging. To increase the recovery rate, use of more than one sensor type in the detection system can be very helpful. High acquisition rates of the sensors ([Kujala et al., 2015](#); [Kutilla et al., 2005](#); [Lukka et al., 2014](#); [Martínez et al., 2012](#)) can be combined with available onboard computational power to develop effective systems. Sensor fusion in the area of recyclable detection from mixed waste includes the following technical challenges:
  - Physical integration of sensors with the sorting systems: Most of the automated systems in this article are single sensor based systems. To identify the target waste material from an unknown environment is a non-trivial task. Focus has to be made in the proper integration of sensors at a particular location to identify and swiftly remove targeted fractions from a moving belt ([Kujala et al., 2015](#); [Lukka et al., 2014](#)). In particular, the

sensors should be integrated into the sorting platform such that sensor cross sensitivity is minimized and the overall design and fabrication is simple.

- Data fusion: Data fusion aims to overcome the limitations of individual sensors and produce accurate, reliable and robust estimation of the world state based on multisensory information (Hu and Gan, 2005). During multi-sensing operation, there are issues such as data modality, data correlation, data alignment, data association, and operational timing which make data fusion a challenging task (Khaleghi et al., 2013). Some key data fusions techniques are Bayesian inference, Markov random fields, Egomotion estimation, and Dempster–Shafer evidence theory (Axenie and Conradt, 2015; Khaleghi et al., 2013; Zhu and Basir, 2006).

(ii) *Energy-efficiency for automated systems:* An energy-efficient automated robotic system needs to be developed for recovering recyclable fractions from landfill sites. In vast landfill sites a robotic waste sorting system needs to operate for extended periods which require long term autonomy. The following challenges need to be tackled for imparting long term autonomy.

- Efficient motion planning: To improve the efficiency of power consumption during search and identification processes, an efficient motion planning and obstacle avoidance needs to be developed for a robotic system. The robot has to negotiate through the static (trees, rocks, etc.) and dynamic (humans, animals, etc.) obstacles and follow an optimum trajectory using various motion planning algorithms (Fujimura, 2012). One of the main challenges in motion planning is the disturbance caused by dynamic obstacles. Intelligent motion planning algorithms need to be developed to generate trajectory plans to deal with obstacles (Švec et al., 2014; Thakur et al., 2012).
- Robotic swarm based efficient waste sorting: Swarm based robotic systems can operate in teams and complement their individual capabilities (Barca and Sekercioglu, 2013; Brambilla et al., 2013; Patil et al., 2015). These robots have usually been tested in confined environments. However, in real world applications limited number of tests have been performed and the reported systems usually fail (Brambilla et al., 2013). To develop fail-safe systems, researchers have to develop swarm robots to tackle real-world applications like sorting and segregating recyclable waste from landfill sites, with proper coordination in motion behavior, precise navigation, and reduced energy consumption under the influence of wind and treacherous terrains (Brambilla et al., 2013).

(iii) *Robust operation under adverse environments:* The robotic systems must be capable of navigating through unknown hostile terrains (Ellery, 2005). The system must not lose stability in the case of breakdowns. The robustness of the robotic systems needs to be improved by expanding the range of operating conditions for different subsystems of the robot. Some of the challenges for improving the robustness are as follows:

- Adverse environment of landfill sites: To sort/segregate the recyclable fractions from MSW in a landfill site, the robot must be capable of handling the recyclables under adverse environments like soft terrain, moisture, wind, and dust. Due to environmental factors such as dust, sensor readings may become error-prone and thus the accuracy of mapping and recognition may get hampered (Vasilyev et al., 2015). In addition, changes in weather conditions during the operation may affect the motion of the robot performing recycling. This can be taken care of via motion planning techniques developed for handling environmental disturbances (Thakur et al., 2012).
- Dynamic obstacles: A large variety of dynamic obstacles are present in a landfill site such as humans, animals, and other vehicles. The robots should be capable of mitigating the dynamic obstacles (Fujimura, 2012).

A large body of literature has been reported in the area of automated industrial level sorting systems targeted for source-separated MSW in a regulated factory environment. A need to deal with mixed waste in large landfill sites in developing countries is opening up new research challenges for the development of robotic systems that can efficiently perform autonomous waste sorting.

### **Acknowledgement**

Authors would like to thank Alexander Weissman, PhD student, Indiana University and Adam Montjoy, Analyst, United States Postal Service for painstakingly proofreading and providing insightful suggestions to improve this paper.

### **References**

- ADB, Asian Development Bank, 2013. Solid waste management in Nepal: current status and policy recommendations. Asian Development Bank, Mandaluyong, Philippines, 2013.
- Afsari, F., 2008. Method of and apparatus for multi-stage sorting of glass cullets. U.S. Patent 7,355,140.
- Afsari, F., Dimsdale, J.S., 2008. Method of and apparatus for high speed, high quality, contaminant removal and color sorting of glass cullet. U.S. Patent 7,351,929.
- Al-Salem, S.M., Lettieri, P., Baeyens, J., 2009. Recycling and recovery routes of plastic solid waste (PSW): A review. *Waste Manage.* 29 (10), 2625–2643.
- Annepu, R.K., 2012. Sustainable solid waste management in India. Columbia University, New York.
- Anzano, J., Casanova, M.E., Bermúdez, M.S., Lasheras, R.J., 2006. Rapid characterization of plastics using laser-induced plasma spectroscopy (LIPS). *Polym. Test.* 25 (5), 623–627.
- Anzano, J., Lasheras, R.J., Bonilla, B., Casas, J., 2008. Classification of polymers by determining of C 1: C 2: CN: H: N: O ratios by laser-induced plasma spectroscopy (LIPS). *Polym. Test.* 27 (6), 705–710.

- Aono, Y., Ando, K., Hattori, N., 2012. Rapid identification of CCA-treated wood using laser-induced breakdown spectroscopy. *J. Wood Sci.* 58 (4), 363–368.
- Axenie, C., Conradt, J., 2015. Cortically inspired sensor fusion network for mobile robot ego-motion estimation. *Robot. Auton. Syst.* 71, 69–82.
- Badgie, D., Samah, M.A., Manaf, L.A., Muda, A.B., 2012. Assessment of municipal solid waste composition in Malaysia: Management, practice and challenges. *Pol. J. Environ. Stud.* 21 (3), 539–547.
- Banar, M., Cokaygil, Z., Ozkan, A., 2009. Life cycle assessment of solid waste management options for Eskisehir, Turkey. *Waste Manage.* 29 (1), 54–62.
- Barca, J.C., Sekercioglu, Y.A., 2013. Swarm robotics reviewed. *Robotica.* 31 (03), 345–359.
- Bakker, E.J., Rem, P.C., Fraunholz, N., 2009. Upgrading mixed polyolefin waste with magnetic density separation. *Waste Manage.* 29 (5), 1712–1717.
- Bezati, F., Froelich, D., Massardier, V., Maris, E., 2010a. Addition of tracers into the polypropylene in view of automatic sorting of plastic wastes using X-ray fluorescence spectrometry. *Waste Manage.* 30 (4), 591–596.
- Bezati, F., Massardier, V., Froelich, D., Maris, E., Balcaen, J., 2010b. Elaboration and characterization of traced polypropylene with rare earth oxides for automatic identification and sorting of end-of-life plastics. *Waste Biomass Valor.* 1 (3), pp.357–365.
- Bezati, F., Froelich, D., Massardier, V., Maris, E., 2011a. Addition of X-ray fluorescent tracers into polymers, new technology for automatic sorting of plastics: Proposal for selecting some relevant tracers. *Resour. Conserv. Recycl.* 55 (12), 1214–1221.
- Bezati, F., Massardier, V., Balcaen, J., Froelich, D., 2011b. A study on the dispersion, preparation, characterization and photo-degradation of polypropylene traced with rare earth oxides. *Polym. Degrad. Stab.* 96 (1), 51–59.
- Blassino, M., Solo-Gabriele, H., Townsend, T., 2002. Pilot scale evaluation of sorting technologies for CCA treated wood waste. *Waste Manage. Res.* 20 (3), 290–301.
- Bokun, R.C., Osadchii, S.M., 2010. Generalization of dual-energy method for material identification with X-ray introscopy. *J. Synch. Investig.* 4 (4), 591–593.
- Bonifazi, G., Serranti, S., 2006. Imaging spectroscopy based strategies for ceramic glass contaminants removal in glass recycling. *Waste Manage.* 26 (6), 627–639.
- Bonifazi, G., Serranti, S., 2012, *Recycling Technologies*, In: Meyers, R.A. (Ed.), *Encyclopedia of Sustainability Science and Technology*. Springer, LLC, pp.8794–8848.
- Braam, B.C., Van Der Valk, H.J.L., Dalmijn, W.L., 1988. Eddy-current separation by permanent magnets Part II: Rotating disc separators. *Resour. Conserv. Recycl.* 1 (1), 3–17.
- Brambilla, M., Ferrante, E., Birattari, M., Dorigo, M., 2013. Swarm robotics: a review from the swarm engineering perspective. *Swarm Intell.* 7 (1), 1–41.

- Brojboiu, M., Mandache, L., Ivanov, V., 2013. Concerning the selectivity of the experimental device based on eddy currents for the metal waste separation. In: Proceedings of 4th International Symposium on Electrical and Electronics Engineering (ISEEE). (pp. 1–5). IEEE.
- Brunner, S., Fomin, P., Kargel, C., 2015. Automated sorting of polymer flakes: Fluorescence labeling and development of a measurement system prototype. *Waste Manage.* 38, 49–60.
- Buchan, R., Yarar, B., 1995. Recovering plastics for recycling by mineral processing techniques. *JOM.* 47 (2), 52–55.
- Burnley, S.J., 2007. A review of municipal solid waste composition in the United Kingdom. *Waste Manage.* 27 (10), 1274–1285.
- Chiemchaisri, C., Juanga, J.P., Visvanathan, C., 2007. Municipal solid waste management in Thailand and disposal emission inventory. *Environ. Monit. Assess.* 135 (1–3), 13–20.
- Cimpan, C., Maul, A., Jansen, M., Pretz, T., Wenzel, H., 2015. Central sorting and recovery of MSW recyclable materials: a review of technological state-of-the-art, cases, practice and implications for materials recycling. *J. Environ. Manage.* 156, 181–199.
- Cazacliu, B., Sampaio, C.H., Miltzarek, G., Petter, C., Le Guen, L., Paranhos, R., Huchet, F., Kirchheim, A.P., 2014. The potential of using air jigging to sort recycled aggregates. *J. Clean. Prod.* 66, 46–53.
- Damanhuri, E., Handoko, W., Padmi, T., 2014. Municipal Solid Waste Management in Indonesia, in: Pariatamby, A., Tanaka, M. (Eds.), *Municipal Solid Waste Management in Asia and the Pacific Islands*. Springer, Singapore, pp. 139–55.
- De Jong, T.P.R., Dalmijn, W.L., 1997. Improving jigging results of non-ferrous car scrap by application of an intermediate layer. *Int. J. Miner. Process.* 49 (1), 59–72.
- De Jong, T.P.R., Dalmijn, W.L., 2002. X-ray transmission imaging for process optimisation of solid resources. In: Proceedings R: 02, Congress.
- De Jong, T.P.R., Dalmijn, W.L., Kattentidt, H.U.R., 2003. Dual energy X-ray transmission imaging for concentration and control of solids. In: Proceedings of IMPC-2003 XXII International Minerals Processing Conference, Cape Town.
- Doak, A.G., 2000. Optical glass sorting machine and method. U.S. Patent 6,144,004.
- Dodbiba, G., Fujita, T., 2004. Progress in separating plastic materials for recycling. *Phys. Sep. Sci. Eng.* 13 (3-4), 165–182.
- Edjabou, M.E., Jensen, M.B., Götze, R., Pivnenko, K., Petersen, C., Scheutz, C., Astrup, T.F., 2015. Municipal solid waste composition: Sampling methodology, statistical analyses, and case study evaluation. *Waste Manage.* 36, 12–23.
- Ellery, A., 2005. Environment–robot interaction—the basis for mobility in planetary micro-rovers. *Robot. Auton. Syst.* 51 (1), 29–39.
- EOCSSB, Editorial Office of China State Statistical Bureau, 2012. *Statistical yearbook of the Republic of China*.

- EPA, Environmental Protection Agency, 2014. Municipal solid waste generation, recycling, and disposal in the United States: Facts and figures for 2014.
- Fellin, M., Negri, M., Zanuttini, R., 2014. Multi-elemental analysis of wood waste using energy dispersive X-ray fluorescence (ED-XRF) analyzer. *Eur. J. Wood Wood Prod.* 72 (2), 199–211.
- Fraunholz, N., 2004. Separation of waste plastics by froth flotation—a review, part I. *Miner. Eng.* 17 (2), 261–268.
- Fujimura, K., 2012. *Motion Planning in Dynamic Environments*. Springer, Verlag, New York.
- Gaustad, G., Olivetti, E., Kirchain, R., 2012. Improving aluminum recycling: A survey of sorting and impurity removal technologies. *Resour. Conserv. Recycl.* 58, 79–87.
- Gesing, A., Harbeck, H., 2008. Particle sorting of light-metal alloys and expanded use of manufacturing scrap in automotive, marine, and aerospace markets. In: *Proceedings of REWAS 2008, Global Symposium on Recycling, Waste Treatment and Clean Technology*. Cancun, Mexico.
- Gondal, M.A., Hussain, T., Yamani, Z.H., Baig, M.A., 2007. The role of various binding materials for trace elemental analysis of powder samples using laser-induced breakdown spectroscopy. *Talanta*, 72 (2), 642–649.
- Gornushkin, I.B., Ruiz-Medina, A., Anzano, J.M., Smith, B.W., Winefordner, J.D., 2000. Identification of particulate materials by correlation analysis using a microscopic laser induced breakdown spectrometer. *J. Anal. Atom. Spectrom.* 15 (6), 581–586.
- Grzegorzec, M., Schwerbel, D., Balthasar, D., Paulus, D., 2011. Automatic sorting of aluminium alloys based on spectroscopy measures. In: *Proceeding of ÖAGM/AAPR Workshop 2011*.
- Gurell, J., Bengtson, A., Falkenström, M., Hansson, B.A.M., 2012a. Laser induced breakdown spectroscopy for fast elemental analysis and sorting of metallic scrap pieces using certified reference materials. *Spectrochim. Acta B.* 74, 46–50.
- Gurell, J., Lundin, P., Falkenström, M., Bengtson, A., Noharet, B., 2012b. Fast and remote analysis of metals for efficient recycling—a laser spectroscopic setup for automated analysis of metallic scrap pieces. In: *proceeding of Symposium on Photonics and Optoelectronics 2012*.
- Hark, R.R., Harmon, R.S., 2014. Geochemical fingerprinting using LIBS. in: Musazzi, S., Perini, U. (Eds.), *Laser-Induced Breakdown Spectroscopy*, Springer, Berlin Heidelberg, pp. 309–348.
- Hansen, T.L., Jansen, J.L.C., Davidsson, Å, Christensen, T.H., 2007. Effects of pre-treatment technologies on quantity and quality of source-sorted municipal organic waste for biogas recovery. *Waste Manage.* 27 (3), 398–405.
- Hasan, A.R., Schindler, J., Solo-Gabriele, H.M., Townsend, T.G., 2011a. Online sorting of recovered wood waste by automated XRF-technology. Part I: Detection of preservative-treated wood waste. *Waste Manage.* 31 (4), 688–694.
- Hasan, A.R., Solo-Gabriele, H., Townsend, T., 2011b. Online sorting of recovered wood waste by automated XRF-technology: Part II. Sorting efficiencies. *Waste Manage.* 31 (4), 695–704.

- Holloway, C.C., 1989. Method for separation, recovery, and recycling of plastics from municipal solid waste. U.S. Patent 4,844,351.
- Hoornweg, D., Bhada-Tata, P., 2012. What a waste: a global review of solid waste management. The World Bank, Washington DC.
- Hu, H., Gan, J.Q., 2005. Sensors and data fusion algorithms in mobile robotics. Technical Report CSM-422, Department of Computer Science, University of ESSEX, UK.
- Hu, B., 2014. Magnetic Density Separation of Polyolefin Wastes. Doctoral Thesis, TU Delft, Delft University of Technology.
- Huang, J., Pretz, T., Bian, Z., 2010, Intelligent solid waste processing using optical sensor based sorting technology. In: Image and Signal Processing (CISP), 2010 3rd International Congress on (Vol. 4, pp. 1657–1661). IEEE
- Huber, R., Leitner, K., 2014. Method and an apparatus for detecting leaded pieces of glass. U.S. Patent 8,803,020.
- Huber, R. and Pansinger, C., 2011. Method for detecting and sorting glass. U.S. Patent 8,030,589.
- Jacobi, G., Solo-Gabriele, H., Townsend, T., Dubey, B., 2007. Evaluation of methods for sorting CCA-treated wood. *Waste Manage.* 27 (11), 1617–1625.
- Jank, A., Müller, W., Schneider, I., Gerke, F., Bockreis, A., 2015. Waste Separation Press (WSP): A mechanical pretreatment option for organic waste from source separation. *Waste Manage.* 39, 71–77.
- Jansen, M., Feil, A. and Pretz, T., 2012. Recovery of plastics from household waste by mechanical separation. In: Thomé-Kozmiensky, J.K., (Eds.), *Waste Management, Recycling and Recovery*, Vol. 3, TK Verlag, Neuruppin, pp.169–175.
- Kasper, A.C., Juchneski, N.C.d.F., and Veit, H.M., 2015, Mechanical processing, in: Veit, H.M., Moura Bernardes, A. (Eds.), *Electronic Waste: Recycling Techniques*, Springer, New York, pp. 19–38.
- Kassouf, A., Maalouly, J., Rutledge, D.N., Chebib, H., Ducruet, V., 2014. Rapid discrimination of plastic packaging materials using MIR spectroscopy coupled with independent components analysis (ICA). *Waste Manage.* 34 (11), 2131–2138.
- Kawai, K., Tasaki, T., 2016. Revisiting estimates of municipal solid waste generation per capita and their reliability. *J. Mater. Cycles Waste Manage.* 18 (1), 1–13.
- Kelland, D., Kolm, H., Maxwell, E. and Oberteuffer, J., 1974. High Gradient Magnetic Separation: An Industrial Application of Magnetism, in: Foner, S., Schwartz, B.B. (Eds.), *Superconducting Machines and Devices*. Springer, US, pp. 581–594.
- Khaleghi, B., Khamis, A., Karray, F.O., Razavi, S.N., 2013. Multisensor data fusion: A review of the state-of-the-art. *Inform. Fusion.* 14 (1), 28–44.

- Khatib, I.A., 2011. Municipal solid waste management in developing countries: Future challenges and possible opportunities, in: Kumar, S., (Ed.), *Integrated Waste Management-Volume II*, InTech.
- Koyanaka, S., Kobayashi, K., 2010. Automatic sorting of lightweight metal scrap by sensing apparent density and three-dimensional shape. *Resour. Conserv. Recycl.* 54 (9), 571–578.
- Koyanaka, S., Kobayashi, K., 2011. Incorporation of neural network analysis into a technique for automatically sorting lightweight metal scrap generated by ELV shredder facilities. *Resour. Conserv. Recycl.* 55 (5), 515–523.
- Kreindl, G 2011, *Sorting of Mixed Commercial Waste for Material Recycling*. In: *Proceeding of TAKAG 2011 - Deutsch-Türkische Abfalltage*, Stuttgart.
- Krivtsova, G.B., Pimenov, A.N., Petukhov, V.V., 2009. Electromagnetic separation of nonferrous metals before a metallurgical conversion in a field of high-frequency current. *Metallurgist.* 53 (78), 524–530.
- Kujala, J.V., Lukka, T.J., Holopainen, H., 2015. Picking a Conveyor Clean by an Autonomously Learning Robot. arXiv: 1511.07608 CS.
- Kutilla, M., Viitanen, J., Vattulainen, A., 2005, Scrap metal sorting with colour vision and inductive sensor array. In: *Proceeding of Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC)*, (2), pp. 725-729.
- Liu, C., Wu, X.W., 2010. Factors influencing municipal solid waste generation in China: a multiple statistical analysis study. *Waste Manage. Res.* 29, 371–378.
- Li, J., Xu, Z., Zhou, Y., 2007. Application of corona discharge and electrostatic force to separate metals and nonmetals from crushed particles of waste printed circuit boards. *J. Electrostat.* 65 (4), 233–238.
- Li, J., Wu, G., Xu, Z., 2015. Tribo-charging properties of waste plastic granules in process of tribo-electrostatic separation. *Waste Manage.* 35, 36–41.
- Lowell, J., Rose-Innes, A.C., 1980. Contact electrification. *Adv. Phys.* 29 (6), 947–1023.
- Luciani, V., Bonifazi, G., Rem, P., Serranti, S., 2015. Upgrading of PVC rich wastes by magnetic density separation and hyperspectral imaging quality control. *Waste Manage.* 45, 118–125.
- Lukka, T.J., Tossavainen, T., Kujala, J.V., Raiko, T., 2014. ZenRobotics recycler–robotic sorting using machine learning. In: *Proceedings of International Conference on Sensor-Based Sorting (SBS)*.
- Martínez, S.S., Paniza, J.L., Ramírez, M.C., Ortega, J.G., García, J.G., 2012. A sensor fusion-based classification system for thermoplastic recycling. In: *Proceeding of 18th International Conference on Automation and Computing (ICAC 2012)*, pp. 1–6.
- Masood, M., Barlow, C.Y., Wilson, D.C., 2014. An assessment of the current municipal solid waste management system in Lahore, Pakistan. *Waste Manage. Res.* 32 (9), 834–847.

- Mesina, M.B., De Jong, T.P.R., Dalmijn, W.L., 2003. Improvements in separation of non-ferrous scrap metals using an electromagnetic sensor. *Phys. Sep. Sci. Eng.* 12 (2), 87–101.
- Mesina, M.B., De Jong, T.P.R., Dalmijn, W.L., 2007. Automatic sorting of scrap metals with a combined electromagnetic and dual energy X-ray transmission sensor. *Int. J. Miner. Process.* 82 (4), 222–232.
- MfE, Ministry for the Environment, 2009. Solid waste composition, environmental report card. Technical report, New Zealand.
- Montejo, C., Costa, C., Ramos, P., del Carmen Márquez, M., 2011. Analysis and comparison of municipal solid waste and reject fraction as fuels for incineration plants. *Appl. Therm. Eng.* 31 (13), 2135–2140.
- Moskal, T.M., Hahn, D.W., 2002. On-line sorting of wood treated with chromated copper arsenate using laser-induced breakdown spectroscopy. *Appl. Spectrosc.* 56 (10), 1337–1344.
- Muchova, L., Bakker, E., Rem, P., 2009. Precious metals in municipal solid waste incineration bottom ash. *Water Air Soil Pollut. Focus.* 9 (1–2), 107–116.
- Noll, R., Bette, H., Brysch, A., Kraushaar, M., Mönch, I., Peter, L., Sturm, V., 2001. Laser-induced breakdown spectrometry—applications for production control and quality assurance in the steel industry. *Spectrochim. Acta B.* 56 (6), 637–649.
- Noll, R., Sturm, V., Aydin, Ü., Eilers, D., Gehlen, C., Höhne, M., Lamott, A., Makowe, J., Vrengor, J., 2008. Laser-induced breakdown spectroscopy—from research to industry, new frontiers for process control. *Spectrochim. Acta B.* 63 (10), 1159–1166.
- Oberteuffer, J., 1973. High gradient magnetic separation. *IEEE Trans. Magn.* 9 (3), 303–306.
- OECD, Organization for Economic Co-operation and Development, 2012. Municipal waste, generation and treatment.
- Ohara, T., Kumakura, H., Wada, H., 2001. Magnetic separation using superconducting magnets. *Physica C.* 357, 1272–1280.
- Parasuraman, R., Sheridan, T.B., Wickens, C.D., 2000. A model for types and levels of human interaction with automation. *IEEE Trans. Syst. Man Cybern. Part A Syst. Humans.* 30 (3), 286–297.
- Patachia, S., Moldovan, A., Tiorean, M., Baltes, L., 2011. Composition determination of the Romanian municipal plastics wastes. In: *Proceeding of the 26th International Conference on Solid Waste Technology and Management.*
- Patil, M., Abukhalil, T., Patel, S., Sobh, T., 2015. Hardware architecture review of swarm robotics system: Self reconfigurability, self reassembly and self replication, in: Sobh, T., Elleithy, K. (Eds.), *Innovations and Advances in Computing, Informatics, Systems Sciences, Networking and Engineering*, Springer International Publishing, Switzerland, pp. 433–444.
- Paulraj, S.G., Hait, S., Thakur, A., 2016. Automated municipal solid waste sorting for recycling using a mobile manipulator. In: *International Design Engineering Technical Conferences and*

- Computers and Information in Engineering Conference (IDETC/CIE), 2016 ASME Conference.
- Pham, D.T. and Alcock, R.J., 2002. *Smart inspection systems: Techniques and applications of intelligent vision*, Amsterdam, Boston: Academic Press.
- Picón, A., Ghita, O., Whelan, P.F., Iriondo, P.M., 2009. Fuzzy spectral and spatial feature integration for classification of nonferrous materials in hyperspectral data. *IEEE Trans. Ind. Inf.* 5 (4), 483–494.
- Picón, A., Ghita, O., Iriondo, P.M., Bereciartua, A., Whelan, P.F., 2010. Automation of waste recycling using hyperspectral image analysis. In: *Emerging Technologies and Factory Automation (ETFA)*, 2010 IEEE Conference. IEEE, pp. 1–4.
- Picon, A., Ghita, O., Rodriguez-Vaamonde, S., Iriondo, P.M., Whelan, P.F., 2011. Biologically-inspired data decorrelation for hyper-spectral imaging. *EURASIP J. Adv. Signal Process.* (1), 1–10.
- Picón, A., Ghita, O., Bereciartua, A., Echazarra, J., Whelan, P.F., Iriondo, P.M., 2012. Real-time hyperspectral processing for automatic nonferrous material sorting. *J. Electron. Imaging.* 21 (1), 013018–1.
- Pita, F., Castilho, A., 2016. Influence of shape and size of the particles on jigging separation of plastics mixture. *Waste Manage.* 48, 89–94.
- Pieber, S., Meirhofer, M., Ragossnig, A., Brooks, L., Pomberger, R., Curtis, A., 2010. Advanced waste-splitting by sensor based sorting on the example of the MT-Plant oberlaa. In: *Tagungsband zur 10. DepoTech Konferenz.* pp. 695–698.
- Rahman, M.O., Hussain, A., Scavino, E., Hannan, M.A. and Basri, H., 2009. Recyclable waste paper sorting using template matching, in: Zaman, H.B., Robinson, P., Petrou, M., Olivier, P., Schröder, H., Shih, T.K. (Eds.), *Visual Informatics: Bridging Research and Practice*. Springer Berlin Heidelberg. pp. 467–478.
- Rahman, M.O., Hussain, A., Basri, H., 2014. A critical review on waste paper sorting techniques. *Int. J. Environ. Sci. Technol.* 11 (2), 551–564.
- Rahman, M.A., Bakker, M.C.M., 2012. Hybrid sensor for metal grade measurement of a falling stream of solid waste particles. *Waste Manage.* 32 (7), 1316–1323.
- Rahman, M.O., Hussain, A., Scavino, E., Hannan, M.A., Basri, H., 2009. Segregating recyclable waste papers using co-occurrence features. In: *Proceeding of the 9th WSEAS international conference on applied computer science (ACS 2009)*, pp. 187–191.
- Rahman, M.O., Hussain, A., Basri, N.E.A., Scavino, E., Basri, H., Hannan, M.A., 2010. Waste paper grade identification system using window features. *J. Comput. Inf. Syst.* 6 (7), 2077–2091.
- Rahman, M.O., Hussain, A., Scavino, E., Basri, H., Hannan, M.A., 2011. Intelligent computer vision system for segregating recyclable waste papers. *Expert Sys. Appl.* 38 (8), 10398–10407.

- Rahman, M.O., Hussain, A., Scavino, E., Hannan, M.A., Basri, H., 2012a. Object identification using DNA computing algorithm. In: Proceeding of Evolutionary Computation (CEC), 2012 IEEE Congress. IEEE, pp. 1–7.
- Rahman, M.O., Hussain, A., Scavino, E., Hannan, M.A., Basri, H., 2012b. Real-time waste paper grading using CBR approach. *Int. J. Innov. Compu. Inf. Control.* 8 (1), 471–488.
- Randell, P., Pickin, J. and Grant, B., 2014. Waste generation and resource recovery in Australia. <http://www.environment.gov.au/system/files/resources/4b666638-1103-490e-bdef-480581a38d93/files/wgrra.pdf>
- Rao, S.R., 2006a. Chapter 7 - Metal Recycling, Waste Management Series, Elsevier, (Vol. 7), pp.167–268.
- Rao, S.R., 2006b. Resource Recovery and Recycling from Metallurgical Wastes. Elsevier, London.
- Rem, P.C., Di Maio, F., Hu, B., Houzeaux, G., Baltés, L., Tieren, M., 2012. Magnetic fluid equipment for sorting of secondary polyolefins from waste. In: Proceeding of Ecoimpuls 2012: International Conference of Environmental Research and Technology, Timisoara, Romania.
- Rem, P.C., Beunder, E.M. and Van den Akker, A.J., 1998. Simulation of eddy-current separators. *IEEE Trans. Magn.* 34 (4), 2280–2286.
- Richard, G.M., Mario, M., Javier, T., Susana, T., 2011. Optimization of the recovery of plastics for recycling by density media separation cyclones. *Resour. Conserv. Recycl.* 55 (4), 472–482.
- Roman, W.C., 1992. Solid waste sorting system. U.S. Patent 5,101,977.
- Sadat-Shojai, M., Bakhshandeh, G.R., 2011. Recycling of PVC wastes. *Polym. Degrad. Stab.* 96 (4), 404–415.
- Saeed, M.O., Hassan, M.N., Mujeebu, M.A., 2009. Assessment of municipal solid waste generation and recyclable materials potential in Kuala Lumpur, Malaysia. *Waste Manage.* 29 (7), 2209–2213.
- Safavi, S.M., Masoumi, H., Mirian, S.S., Tabrizchi, M., 2010. Sorting of polypropylene resins by color in MSW using visible reflectance spectroscopy. *Waste Manage.* 30 (11), 2216–2222.
- Shapiro, M., Galperin, V., 2005. Air classification of solid particles: a review. *Chem. Eng. Process. Process Intensif.* 44 (2), 279–285.
- Satchell, P., 1998. Innovation and automation. Ashgate Publishing.
- Sattler, H., 1990. Automatic sorting of non-ferrous metals from automobile shredders. In: Proceeding of 2nd International Symposium on Recycling of Metals and Engineered Materials, pp. 333–341.
- Sattler, H., Yoshida, T., 1993. New sorting system for recycling of magnesium and its alloys after use. In: Proceeding of 1st International Conference on Processing Materials for Properties, pp. 861–864.

- Schlömann, E., 1975. Separation of nonmagnetic metals from solid waste by permanent magnets. I. Theory. *J. Appl. Phys.* 46 (11), 5012–5021.
- Serranti, S., Bonifazi, G., Pohl, R., 2006. Spectral cullet classification in the mid-infrared field for ceramic glass contaminants detection. *Waste Manage. Res.* 24 (1), 48–59.
- Serranti, S., Gargiulo, A., Bonifazi, G., 2010. The utilization of hyperspectral imaging for impurities detection in secondary plastics. *Open Waste Manage. J.* 3, 56–70.
- Serranti, S., Gargiulo, A., Bonifazi, G., 2011. Characterization of post-consumer polyolefin wastes by hyperspectral imaging for quality control in recycling processes. *Waste Manage.* 31 (11), 2217–2227.
- Serranti, S., Gargiulo, A., Bonifazi, G., 2012. Classification of polyolefins from building and construction waste using NIR hyperspectral imaging system. *Resour. Conserv. Recycl.* 61, 52–58.
- Sharma, M., McBean, E., 2007. A methodology for solid waste characterization based on diminishing marginal returns. *Waste Manage.* 27 (3), 337–344.
- Solo-Gabriele, H.M., Townsend, T.G., Hahn, D.W., Moskal, T.M., Hosein, N., Jambeck, J., Jacobi, G., 2004. Evaluation of XRF and LIBS technologies for on-line sorting of CCA-treated wood waste. *Waste Manage.* 24 (4), 413–424.
- Švec, P., Thakur, A., Raboin, E., Shah, B.C., 2014. Target following with motion prediction for unmanned surface vehicle operating in cluttered environments. *Auton. Robot.* 36 (4), 383–405.
- Svoboda, J., 2004. *Magnetic Techniques for the Treatment of Materials*. Springer.
- Svoboda, J., Fujita, T., 2003. Recent developments in magnetic methods of material separation. *Miner. Eng.* 16 (9), 785–792.
- Takemura, Y., Fuchikawa, Y., Kurogi, S., Ito, S., Obata, M., Hiratsuka, N., Miyagawa, H., Watanabe, Y., Suehiro, T., Kawamura, Y., Ohkawa, F., 2006. Development of a sensor system for outdoor service robot. In: *SICE-ICASE 2006, International Joint Conference*, pp. 2687–2691.
- Takezawa, T., Uemoto, M., Itoh, K., 2015. Combination of X-ray transmission and eddy-current testing for the closed-loop recycling of aluminum alloys. *J. Mater. Cycles Waste Manage.* 17 (1), 84–90.
- Takoungsakdakun, T., Pongstabodee, S., 2007. Separation of mixed post-consumer PET–POM–PVC plastic waste using selective flotation. *Sep. Purif. Technol.* 54 (2), 248–252.
- Tam, V.W., 2008. Economic comparison of concrete recycling: A case study approach. *Resour. Conserv. Recycl.* 52 (5), 821–828.
- Tatzer, P., Wolf, M., Panner, T., 2005. Industrial application for inline material sorting using hyperspectral imaging in the NIR range. *Real-Time Imaging*, 11 (2), 99–107.

- Thakur, A., Svec, P., Gupta, S.K., 2012. GPU based generation of state transition models using simulations for unmanned surface vehicle trajectory planning. *Robot. Auton. Syst.* 60 (12), 1457–1471.
- Uhl, A., Loebe, K., Kreuchwig, L., 2001. Fast analysis of wood preservers using laser induced breakdown spectroscopy. *Spectrochim. Acta B.* 56 (6), 795–806.
- UNEP, United Nations environment programme, 2012. Waste investing in energy and resource efficiency.
- Vajna, B., Palásti, K., Bodzay, B., Toldy, A., Patachia, S., Buican, R., Catalin, C., Tierean, M., 2010. Complex analysis of car shredder light fraction. *Open Waste Manage. J.* 2 (53), 2–50.
- Vasilyev, I., Kashourina, A., Krashennnikov, M., Smirnova, E., 2015. Use of mobile robots groups for rescue missions in extreme climatic conditions. *Procedia Eng.* 100, 1242–1246.
- Vegas, I., Broos, K., Nielsen, P., Lambertz, O., Lisbona, A., 2015. Upgrading the quality of mixed recycled aggregates from construction and demolition waste by using near-infrared sorting technology. *Constr. Build. Mater.* 75, 121–128.
- Von Ketelhodt, L., Bergmann, C., 2010. Dual energy X-ray transmission sorting of coal. *J. South Afr. Inst. Min. Metall.* 110 (7), 371.
- Watada, J., 2008. DNA computing and its applications. In: *Proceeding of Intelligent Systems Design and Applications (ISDA), 2008 International Conference.* IEEE, pp. 288–294.
- Wang, C.Q., Wang, H., Liu, Q., Fu, J.G., Liu, Y.N., 2014. Separation of polycarbonate and acrylonitrile–butadiene–styrene waste plastics by froth flotation combined with ammonia pretreatment. *Waste Manage.* 34 (12), 2656–2661.
- Wang, C.Q., Wang, H., Fu, J.G., Liu, Y.N., 2015. Flotation separation of waste plastics for recycling—A review. *Waste Manage.* 41, 28–38.
- Wang, H., Chen, X.L., Bai, Y., Guo, C., Zhang, L., 2012. Application of dissolved air flotation on separation of waste plastics ABS and PS. *Waste Manage.* 32 (7), 1297–1305.
- Wu, G., Li, J., Xu, Z., 2013. Triboelectrostatic separation for granular plastic waste recycling: A review. *Waste Manage.* 33 (3), 585–597.
- Yeh, C.W., Chu, C.P., 2008. Molecular verification of rule-based systems based on DNA computation. *IEEE Trans. Knowl. Data Eng.* 20 (7), 965–975.
- Yuan, H., Fu, S., Tan, W., He, J., Wu, K., 2015. Study on the hydrocyclonic separation of waste plastics with different density. *Waste Manage.* 45, 108–111.
- Zhu, H., Basir, O., 2006. A novel fuzzy evidential reasoning paradigm for data fusion with applications in image processing. *Soft Computing*, 10 (12), 1169–1180.