

1 **Critical review of real-time methods for solid waste characterisation: informing**  
2 **material recovery and fuel production**

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9

10 **Abstract:** Waste management processes generally represent a significant loss of material, energy and  
11 economic resources, so legislation and financial incentives are being implemented to improve the  
12 recovery of these valuable resources whilst reducing contamination levels. Material recovery and  
13 waste derived fuels are potentially valuable options being pursued by industry, using mechanical and  
14 biological processes incorporating sensor and sorting technologies developed and optimised for  
15 recycling plants. In its current state, waste management presents similarities to other industries that  
16 could improve their efficiencies using process analytical technology tools. Existing sensor  
17 technologies could be used to measure critical waste characteristics, providing data required by  
18 existing legislation, potentially aiding waste treatment processes and assisting stakeholders in decision  
19 making. Optical technologies offer the most flexible solution to gather real-time information  
20 applicable to each of the waste mechanical and biological treatment processes used by industry. In  
21 particular, combinations of optical sensors in the visible and the near-infrared range from 800 nm to  
22 2500 nm of the spectrum, and different mathematical techniques, are able to provide material  
23 information and fuel properties with typical performance levels between 80% and 90%. These sensors  
24 not only could be used to aid waste processes, but to provide most waste quality indicators required  
25 by existing legislation, whilst offering better tools to the stakeholders.

26

27 **Keywords:** *Solid waste; real-time sensors; waste derived fuel; energy from waste; waste*  
28 *analysis*

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30

## 31 1 INTRODUCTION

32 Changes in legislation and the introduction of economic incentives are promoting the recovery of  
33 valuable resources and the reduction of landfill waste disposal (Council of the European Union,  
34 1999). Sustainable options for waste management are being investigated with a focus on optimising  
35 the recovery of recyclable materials. Residual waste, which is not viable for being reused or recycled,  
36 contains calorific value which could partially displace fossil-derived fuels (European Parliament.,  
37 2009), and the recovery of this energy is a sustainable option, and certainly more manageable, when  
38 compared to landfill biogas (Jeswani and Azapagic, 2016). Therefore, waste is considered a valuable  
39 resource with potential of being a major energy contributor (Slade et al., 2011), and many innovations  
40 are being introduced to retrieve this energy efficiently (Baytekin et al., 2013; Lombardi et al., 2015).  
41 In Europe, energy recovery from waste is one of the recommended operations by the existing legal  
42 framework (Council of the European Union., 2008) to reduce landfill use.

43 Waste (or refuse)- derived fuel (WDF or RDF) is defined as '*a heterogeneous group of non-*  
44 *hazardous wastes that do not cease to be such by virtue of their being used to generate energy without*  
45 *a greater negative environmental impact than landfill disposal*' (WRAP, 2012a). Refuse-derived fuels  
46 are prepared by processing waste materials from municipal, industrial and commercial sources, and  
47 they are typically used in co-incineration plants in different industries, such as cement kilns and  
48 power stations (Lorber et al., 2012; Sarc and Lorber, 2013). In contrast, solid recovered fuel (SRF) is  
49 a term used by waste industry to indicate a composition of waste derived fuel which meets strict  
50 quality specifications. Existing SRF standards at European and UK levels allow authorities, waste  
51 management service providers and equipment manufacturers to work together in a regulated  
52 environment.

53 The European Committee for Standardization (CEN) and Technical Committee (TC) established the  
54 standard specifications and requirements for SRF (European Committee for Standardization, 2012). A  
55 total of 33 standards and reports were published to cover all the different aspects involved in SRF  
56 quality assurance, such as determination of calorific value and moisture contents, and methods for  
57 sampling (British Standards Institution, 2011a, 2011b, 2011c). The main indicators used by the

58 CEN/TC 343 standards to characterise SRF are the net calorific value (NCV), the chlorine (Cl)  
59 content, and the mercury (Hg) content, which point to the economic, technical, and environmental  
60 quality of the fuel, respectively (British Standards Institution, 2011d).

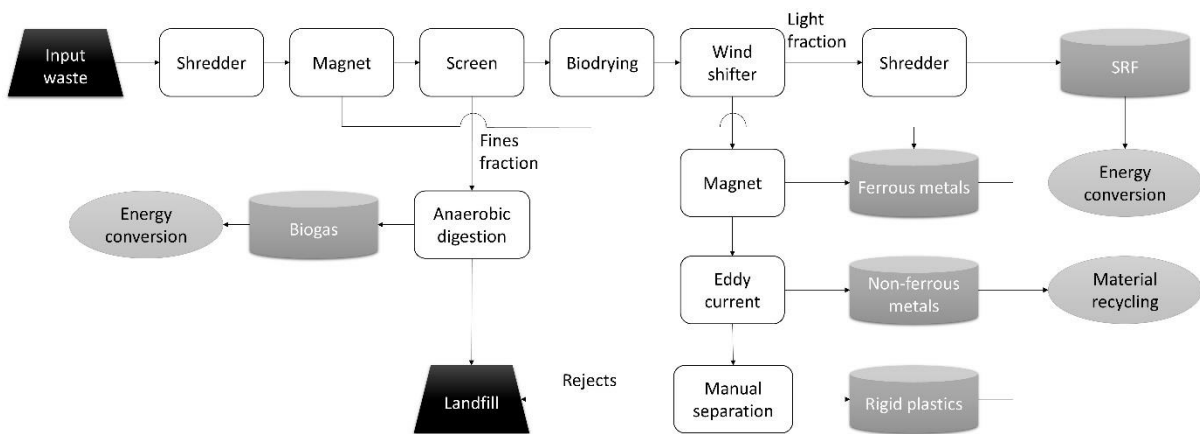
61 The most adopted waste management strategy is to implement material recovery facilities (MRFs)  
62 (Velis et al., 2010) to process municipal solid waste (MSW) and refuse from commercial and  
63 industrial (C&I) or from construction and demolition (C&D) sources. An important goal of a MRF is  
64 to reduce the waste volume and mass before sending it to a landfill. Outputs from a MRF can include  
65 high-calorific material such as RDF and SRF, recyclable materials such as metals, and stabilised  
66 organic waste which could be used as fertiliser. Implementation of the correct waste treatment  
67 processes together with quality assurance are key to obtain the highest possible waste-derived fuel  
68 quality, and these are affected by the input waste and desired output properties (Lorber et al., 2012;  
69 Sarc et al., 2014; Sarc and Lorber, 2013). Data informing on waste processes, including flows,  
70 treatment efficiencies and timings are required by stakeholders to create new policies and improve  
71 waste treatment (RWM Ambassadors, 2016).

72 The composition of mixed solid waste is highly variable, including different materials and  
73 contaminant levels, which represents a challenge to MRF to meet the required RDF and SRF qualities  
74 with consistency (Cimpan et al., 2015; Flamme and Geiping, 2012). Currently, the waste received is  
75 processed through a combination of manual sorting, and mechanical and biological technologies  
76 (MBT) which are selected according to the type of input waste and desired output characteristics  
77 (DEFRA, 2013; Velis et al., 2010). The plants are designed to balance manual sorting processes, with  
78 high efficiency but increased labour costs, and automated sorting processes, which require more  
79 investment capital (Tchobanoglous and Kreith, 2002; WRAP, 2006).

80 Input waste is received into a tipping hall, where it is stored protected from the weather for up to two  
81 days (WRAP, 2007). The transport of waste from one process unit to another is typically done with  
82 conveyor belts, whilst input waste is loaded with grabbing cranes and output material is moved with  
83 fork lifts and wheel loaders (Tchobanoglous and Kreith, 2002). An illustration of the typical waste  
84 flow between manual, mechanical and biological treatment processes is depicted in Figure *1*.

85 Due to the difficulties and limitations of these processes to separate materials and sort them based on  
 86 grades, to obtain high quality waste-derived fuel (Cimpan et al., 2015; Rotter et al., 2004), advanced  
 87 sensors are being developed to improve and complement these methods. These new technologies are  
 88 required to adapt to short- and long-term changes in waste composition, introduction of new materials  
 89 and increasing legal requirements (Cimpan et al., 2015). Stakeholders, particularly in developing  
 90 countries, prefer waste management systems with high efficiency and lower costs (Guerrero et al.,  
 91 2013). The integration of multiple sensors, improved energy efficiency, and ruggedness to withstand  
 92 the extreme environment conditions are some of the technical challenges to be faced by future  
 93 research and development in this subject (Gundupalli et al., 2016).

94



95

96 **Figure 1.** Flow sheet diagram of a typical MRF using manual and MBT processes to produce  
 97 four outputs: biogas and SRF for energy conversion, materials for recycling, and rejects  
 98 going into landfill. Adapted from DEFRA (2013).

99

## 100 1.1 MANUAL SORTING

101 Hand picking or manual sorting is a physical operation performed by plant personnel working in  
 102 special facilities installed at different waste processing stages. The goal is to either sort the waste  
 103 items based on material type, or to remove those items that could reduce the performance of other  
 104 processes downstream (Tchobanoglous and Kreith, 2002). Humans have a unique ability to recognise

105 materials in a very short time (Sharan et al., 2014), with observed waste recovery efficiencies up to  
106 95% (Tchobanoglous and Kreith, 2002). Many factors affect this efficiency, such as fatigue,  
107 circulation speed, particle size distribution and volumetric flow of the waste material, and  
108 environmental aspects such as working temperature and lighting. The overall manual sorting  
109 efficiency is proportional to the number of people performing these tasks, but also requiring larger  
110 facilities.

## 111 **1.2 BIOLOGICAL PROCESSES**

112 Biological processes are applied in a MRF when the input waste stream contains biodegradable  
113 materials, which is typically contained in municipal solid waste (MSW) (Nasrullah et al., 2015).  
114 Waste from commercial and industrial, or from construction and demolition sources do not usually  
115 have a biodegradable fraction (Nasrullah et al., 2014a, 2014b), therefore biological processes are not  
116 required (Velis et al., 2010). There are two main types of biological processes used in MBT systems,  
117 biodrying and anaerobic digestion. With these processes it is possible to reduce the volume of waste  
118 going into landfill, in particular the biodegradable fraction. They can also be used to improve the  
119 quality of the waste derived fuel being produced, to produce stabilised bio-waste to be used as soil  
120 conditioner, or to generate biogas for energy conversion (DEFRA, 2013).

## 121 **1.3 MECHANICAL PROCESSES**

122 Mechanical processes for the preparation of waste material include size reduction (comminution), and  
123 separation based on size, shape, density, and magnetic properties. The performance or efficiency of  
124 the separation processes are defined by their recovery rate and purity grade. Recovery rate is defined  
125 as the ratio of the mass of the particular component appearing in an output fraction and the total mass  
126 of that component in the input stream. The purity grade expresses the level of cleanliness of a  
127 particular component in an output fraction, as the ratio of the mass of the particular component  
128 present in that output fraction and the total mass of that output fraction. Several factors affect the  
129 performance of the different process units, including the moisture level, particle shapes and size  
130 distribution, and the presence of large or hard objects (Table 1).

131 **Table 1.** Mechanical and biological processes, their effects on solid waste streams and  
 132 operational parameters affecting their efficiency.

Process	Main objective	Effects on waste	Factors affecting performance	Main operational variables
<b>Bag splitting</b>	Increase waste stream throughput <sup>1,2</sup>	Enable mechanical separation; increase energy recovery	Presence of large or hard items in the input stream <sup>1,3</sup>	Distance between cutting shears; shears rotational speed <sup>3</sup>
<b>Shredding</b>	Reduce particle size and homogenise waste stream <sup>1,2</sup>	Increase biochemical reactivity; reduce bulk volume; enable mechanical separation; increase energy recovery	Presence of large or hard items in the input stream <sup>1,3</sup>	Distance between cutting shears; shears rotational speed <sup>3</sup>
<b>Screening</b>	Separate a particular shape, and larger from smaller fractions <sup>1,2</sup>	Remove ash and moisture content; increase WDF calorific value <sup>4-7</sup>	Presence of highly ductile material which end up in fines fraction; particle size distribution; throughput <sup>1</sup>	Filter size and shape; residence time <sup>1</sup>
<b>Air separation</b>	Separate lighter from heavier fractions <sup>1,2</sup>	Remove non-combustible material; increase energy recovery <sup>4-7</sup>	Absorbed moisture in light materials which end up in heavy fraction; particle size distribution <sup>8,9</sup>	Distance between separation chambers; air flow rate <sup>9</sup>
<b>Ballistic separation</b>	Separate lighter from heavier, and smaller from larger fractions <sup>1,2</sup>	Remove organics and non-combustible material; increase energy recovery <sup>2,4-6</sup>	Absorbed moisture in light materials which end up in heavy fraction; particle size distribution <sup>2</sup>	Filter size and shape; vibration frequency; inclination angle <sup>2</sup>
<b>Magnetic separation</b>	Separate ferrous metals from waste stream <sup>1,2,10</sup>	Remove non-combustible material; increase energy recovery <sup>1,2,4-6</sup>	Particle size distribution; moisture level <sup>1,10</sup>	Magnetic field strength <sup>1,10</sup>
<b>Eddy current separation</b>	Separate non-ferrous metals from waste stream <sup>1,2,11</sup>	Separate non-combustible material; increase energy recovery <sup>2,12,13</sup>	Particle size distribution; moisture level; presence of aggregated materials; throughput; humidity <sup>1,11,14</sup>	Electric field strength; distance between separation chambers <sup>1,11</sup>
<b>Biodrying</b>	Reduce moisture and waste stream volume <sup>1,2,15</sup>	Increase energy recovery <sup>4-6,15,16</sup>	Moisture level; composition and presence of organic material <sup>16</sup>	Aeration flow; temperature; residence time <sup>16</sup>
<b>Anaerobic digestion</b>	Recover energy and converts biodegradable contents to gas <sup>1,2</sup>	Reduce overall solid mass <sup>1,2</sup>	Particle size distribution; composition; organic material; biochemical methane potential <sup>17-19</sup>	Feed pump flow; buffer substance concentration; heat; pH <sup>17-19</sup>

<sup>1</sup>Tchobanoglous and Kreith (2002), <sup>2</sup>Velis et al.(2010), <sup>3</sup>Fitzgerald and Themelis (2009), <sup>4</sup>Nasrullah et al.(2015), <sup>5</sup>Nasrullah et al.(2014a), <sup>6</sup>Nasrullah et al. (2014b), <sup>7</sup>Cimpan and Wenzel (2013), <sup>8</sup>Rotter et al.(2004), <sup>9</sup>Shapiro and Galperin (2005), <sup>10</sup>Svoboda and Fujita (2003), <sup>11</sup>Rem et al. (1998), <sup>12</sup>Ionescu et al. (2013), <sup>13</sup>Mesina et al.(2007), <sup>14</sup>Jujun et al.(2014), <sup>15</sup>de Araújo Morais et al.(2008), <sup>16</sup>Velis et al. (2009), <sup>17</sup>Zhang and Banks(2013), <sup>18</sup>John and Singh(2011), <sup>19</sup>Sponza and Ağdağ (2005)

133

134 **2 ADVANCED SENSORS**

135 These new types of automated processes use combinations of advanced, non-invasive sensors and

136 mechanical processes to provide fast separation and sorting of materials. Usually, the sensor is used to

137 detect a particular characteristic of a material, classifying it and deciding its destination fraction using  
138 a computer system, and then a mechanical process separates it from the mixed stream accordingly  
139 (Velis et al., 2010). Advanced online processes are fundamental to reliably sort materials, increasing  
140 the waste processing plant efficiency by producing high purity recycled and SRF materials(WRAP,  
141 2010).

## 142 **2.1 FLUORESCENCE**

143 Fluorescence sensors determine the presence of a certain material by measuring the light emission  
144 generated after the material is excited with a light. Of particular interest is the fluorescence property  
145 of lignin to emit light at near 650nm when excited with visible light. For example, some proposed  
146 methods (Ammineni, 2001; Mallapragada, 2004; Ramasubramanian et al., 2005) can separate  
147 newspaper from mixed papers in real-time but the results are affected by coloured paper, with red ink  
148 reflecting light close to the 650nm wavelength which the sensor can confuse with lignin fluorescence,  
149 whilst green and blue inks reduce the lignin fluorescence effect.

## 150 **2.2 HYDROPHOBICITY**

151 By using electrochemical properties of materials, such as their surface hydrophobicity, it is possible to  
152 sort plastics by flotation mechanisms (Fraunholz, 2004; Wang et al., 2015). For example, the method  
153 investigated by Saisinchai (2014) separates polyvinyl chloride (PVC) from polyethylene terephthalate  
154 (PET) plastics using a froth flotation method with calcium lignosulfonate as the wetting reagent. A  
155 review of flotation mechanisms to separate plastics, mainly PVC or PET from polystyrene or  
156 polyethylene was conducted by Wang et al. (2015).

## 157 **2.3 LASER INDUCED BREAKDOWN SPECTROSCOPY**

158 Laser induced breakdown spectroscopy (LIBS) involves focussing a high energy laser onto a material  
159 which generates plasma emissions with a particular light spectrum. These emissions are detected with  
160 a spectrograph and analysed to determine the material chemical composition, such as contaminants.  
161 For example, Barefield et al. (1995) used this technique to detect the presence of Strontium in mixed



162 waste. Similarly, the presence of contaminated waste wood can be detected with LIBS, with  
163 measurement times of 3-5 seconds per sample (Rasem Hasan et al., 2011). A comprehensive list of  
164 detection limits obtained for different chemicals has been published by Zorov et al. (2015). Huber et  
165 al. (2014) investigated the use of LIBS to detect chlorine in industrial waste in real-time, without  
166 being affected by the visible colour of the plastics.

167 The use of LIBS was also explored to identify plastic materials by analysing the emitted plasma to  
168 detect the presence of carbon and hydrogen (Gondal and Siddiqui, 2007). The combination of  
169 different multivariate correlation methods and LIBS were investigated to sort different types of  
170 polymers (Anzano et al., 2011; Banaee and Tavassoli, 2012). Similarly, LIBS was studied by Aguirre  
171 et al. (2013) who characterised polymers and other materials used in electronic equipment. In the  
172 context of metal scrap sorting, LIBS was used to classify aluminium alloys by Werheit (2011), whilst  
173 another project obtained real-time classification of 10 different classes of metal alloys (Merk et al.,  
174 2015).

## 175 **2.4 MICROWAVES**

176 These sensors measure the interaction of electromagnetic fields at microwave frequencies, i.e.  
177 electromagnetic waves, and dielectric materials. For example, resonant sensors can be used to  
178 measure changes in resonant frequencies due to the absorbed water in a moisture sensitive ceramic.  
179 This technique was successfully tested to determine the contents of moisture in construction and  
180 demolition materials (Quinn and Kelly, 2010; Sokoll and Jacob, 2007). Wagland et al. (2013)  
181 investigated the use of microwaves to measure moisture level in mixed solid waste, using a  
182 microwave setup with a transmitter and an array of sensors to detect signal absorption and  
183 transmission in waste materials (wood, cardboard, textile) to estimate their moisture content.

## 184 **2.5 RESISTIVITY AND CAPACITY**

185 This group of sensors can detect changes in electrical fields due to variations of pressure, humidity,  
186 and conductivity. They range from very simple to complex circuitry designs that allow for increased  
187 functionality, such as self-calibration and error compensation. In general, they are low cost, small

188 sized and with low power consumption (Du, 2014). Resistive sensors measure changes in resistivity  
189 between two electrodes when in the presence of conductor media such as water. A proposed method  
190 (Gawande et al., 2003) calibrated a resistive sensor using mixed solid waste. Capacitive sensors  
191 measure the dielectric permittivity of materials between two plates (Udo and Christof, 2010). The  
192 method investigated by Fuchs et al. (2008) measures moisture content in municipal solid waste falling  
193 off a conveyor belt with a capacitive sensor.

## 194 **2.6 STIFFNESS**

195 It is possible to sort paper by using its elastic properties, as discussed by Baum (1987). For example,  
196 one researched method measures the deflection in path trajectory caused by a jet of air to classify  
197 grades of paper based on their different stiffness properties (Katuri, 2006; Ramasubramanian et al.,  
198 2006, 2007). This technique is able to sort paper based on their grades, such as newspaper, office  
199 paper and cardboard, in real-time on a conveyor belt at a speed of 1.5 m/s (Ramasubramanian et al.,  
200 2012).

## 201 **2.7 ULTRASOUND IMAGING**

202 This method sends ultrasound pulses to a material, which reflects or scatters back the ultrasound  
203 waves as they travel through the material, with varying intensity according to the material density. An  
204 ultrasound sensor receives and processes these reflections (ultrasound echoes) to generate an  
205 ultrasound image. A proposed method (Faibish et al., 1997) uses a combination of optical and  
206 ultrasonic sensors to detect and remove paper from municipal waste in real-time. Ultrasound  
207 techniques have also been investigated to recognize and quantify plastic materials in waste in real-  
208 time using a wet medium (Sanaee and Bakker, 2009), showing a marked difference in signal  
209 amplitude between polypropylene and polyethylene materials.

## 210 **2.8 OPTICAL IMAGING USING VISIBLE WAVELENGTH SENSORS**

211 Visible optical sensors are based on the surface properties of materials to reflect varying intensities of  
212 light in wavelengths visible to the human eye (400-700 nm). Visible image sensors, such as

213 complementary metal-oxide semiconductor (CMOS) and charged couple devices (CCD) cameras,  
214 produce images with pixel intensities proportional to the visible light received (Janesick, 2007).  
215 Unique features in the materials and the generated images, such as shape, colour and surface textures  
216 can be used to recognize objects, for example bottles (Nawrocky et al., 2010; Torres-García et al.,  
217 2015; Wahab et al., 2006), cans (Torres-García et al., 2015; Yani and Budiman, 2015), minerals  
218 (Anding et al., 2011, 2013), and electronic boards (Kleber et al., 2015; Torres-García et al., 2015).  
219 Optical imaging has also been studied to determine particle size distributions of different mixed  
220 materials (Bianconi et al., 2015; Nakamura et al., 2005; Salehizadeh and Sadeghi, 2010; Urbanski et  
221 al., 2011). Typical issues affecting these visible optical imaging methods are changes in illumination,  
222 or the presence of different materials or objects presenting similar visible features such as colour.

223 The method investigated by Huang et al. (2010) uses a 3D camera to extract both colour and shape  
224 information to classify waste objects. This setup had a high classification rate for non-ferrous metals,  
225 plastics bottles and coins. Identification of polypropylene and acrylonitrile butadiene styrene had the  
226 highest rate, but the detection of polymers was affected by their surface colours, as only 20% of black  
227 plastics were identified correctly. Rahman et al. (2009a, 2009b, 2010, 2011, 2012b, 2012a, 2012c,  
228 2014, 2015) developed and tested a series of mathematical algorithms to process images acquired with  
229 a colour webcam, separating different grades of paper. Visible image processing was also investigated  
230 to sort wood according to type, colour and quality grades (Bombardier and Schmitt, 2010; Faria et al.,  
231 2008; Hréka, 2008; Kurdthongmee, 2008; Lu et al., 1997).

232 The imaging method developed by Wagland et al. (2012, 2013) captured images of mixed solid waste  
233 to manually identify materials and estimate the waste composition and biogenic energy potential of  
234 waste. This methodology was further researched to estimate the composition of solid recovered fuels  
235 (Peddireddy et al., 2015). These methods used waste composition as a surrogate for estimating the  
236 fuel properties of waste, either at the collection point or at the end of the MBT process, requiring a  
237 database of properties for the individual waste materials.

## 238 **2.9 OPTICAL IMAGING USING INFRARED WAVELENGTH SENSORS**

239 Infrared sensors are able to detect variations in absorption, transmittance and scattering of light in  
240 infrared wavelengths produced by different materials. The infrared spectrum is typically divided into  
241 several regions: near infrared (NIR, wavelengths: 700-1400 nm), short-wave infrared (SWIR,  
242 wavelengths: 1400-3000 nm), medium-wave infrared (MWIR or MIR, wavelengths: 3000-8000 nm),  
243 and long-wave infrared (LWIR or LIR, wavelengths: 8000-15000 nm). Both MIR and LIR methods  
244 require longer acquisition times than NIR and SWIR, but offer more defined spectral information. On  
245 the other hand, acquisition of NIR and SWIR spectra is quicker but they require advanced  
246 mathematical techniques, such as multivariate statistical analysis to extract information about material  
247 components (Reich, 2005).

248 Typical infrared image sensors include CCD cameras, which produce a digital image with pixel  
249 intensities proportional to the infrared light reflected or scattered back by a material in that particular  
250 position. Multispectral imaging or hyperspectral imaging (HSI) methods capture the spectral response  
251 for each pixel in the digital image, which is affected by the material composition for that particular  
252 position. An early multispectral method was developed by Rantanen et al. (1998), using NIR sensors  
253 tuned to 3 different SWIR wavelengths to estimate moisture content in pharmaceutical pellets in real-  
254 time. More recently, the studies by Achata et al. (2013) and by Wünsch and Jenkins (2013) used NIR  
255 hyperspectral imaging to determine moisture content in food and mixed solid waste samples,  
256 respectively.

257 Some methodologies are developed to use more than one region of the light spectrum. For example,  
258 McWhirt et al. (2012) used a visible and near infrared (VIS-NIR) system to determine the contents of  
259 organic matter in compost sourced from different types of feedstock in real-time. Techniques using  
260 NIR-MIR hyperspectral imaging to determine biochemical methane potential from municipal solid  
261 waste were tested with positive results using statistical analysis (Lesteur et al., 2011, 2013), whilst  
262 similar results were obtained by other researchers in the review article by Ward (2016). The utilisation  
263 of NIR-SWIR imaging technology for the recycling of textiles were explored with government and  
264 industry support (European Commission, 2012; Ishfaq, 2015; Luiken and Bos, 2010).

265 Other uses of optical infrared methods are to identify specific substances or materials grades, such as  
266 the investigation of Mauruschat et al. (2015) to use NIR hyperspectral imaging to detect chemical  
267 preservatives and plastics contaminants in wood. Classification of glass contaminants in mixed glass  
268 materials using NIR and MIR spectral imaging was investigated by Farcomeni et al. (2008). Tatzer et  
269 al. (2005) used hyperspectral NIR imaging for the recycling of 4 different grades of cardboard and  
270 paper, and similar methods were investigated to sort materials from construction and demolition  
271 (C&D) sources (Anding et al., 2015; Kuritcyn et al., 2015; Palmieri et al., 2014).

272 Extensive research has been completed on sorting and recycling plastic materials, with early  
273 experiments with NIR hyperspectral imaging to quickly identify plastics from a distance (Huth-Fehre  
274 et al., 1995; van den Broek et al., 1996). Wienke et al. (1996) extended this method and used NIR-  
275 SWIR multispectral analysis to identify plastics from domestic waste. Waste electrical and electronic  
276 equipment (WEEE) contains recyclable plastics which could be sorted by NIR devices (WRAP,  
277 2009). Beigbeder et al. (2013) used NIR-SWIR hyperspectral imaging to sort plastics material from a  
278 WEEE stream with similar results to those presented in the WRAP industry report from 2009. More  
279 recently, techniques using NIR-SWIR hyperspectral imaging have been investigated for separating  
280 fossil-based plastics from the more modern and environmentally friendly bio-plastics (Hollstein and  
281 Wohllebe, 2015).

282 Black or very dark plastics present a problem for optical methods as they absorb most of the light in  
283 VIS, NIR, and SWIR wavelengths and therefore, the reflected spectra do not contain enough  
284 information about the material composition (Huth-Fehre et al., 1995; WRAP, 2011). A potential  
285 solution to the black plastics problem was investigated by Kassouf et al. (2014), who used MIR-LIR  
286 hyperspectral imaging and statistical analysis methods to successfully identify 5 different types of  
287 polymers regardless of their colours.

288 Applications of NIR hyperspectral technology to waste management have been described by Bonifazi  
289 and Serranti (2014), suggesting its feasibility as a quality control tool. The use of NIR spectral  
290 information to directly determine the composition of waste was investigated by Smidt et al. (2008),  
291 using statistical analysis to classify waste into 3 groups: landfill, composts, and MSW. Pieber et al.

292 (2012) investigated the use of commercial NIR sorting devices for the production of SRF, and their  
293 effect on removing chlorine, cadmium and lead contaminants. Krämer and Flamme (2015) presented  
294 the results of an industry sponsored project using NIR hyperspectral imaging and statistical analysis to  
295 determine SRF composition and fuel properties. This method used a database of material properties to  
296 indirectly estimate chlorine, calorific value, and ash contents, as originally described by Wagland et  
297 al. (2013) and Peddireddy et al. (2015).

## 298 **2.10 X-RAY IMAGING**

299 X-ray is a form of high energy radiation which can penetrate materials, where it is absorbed or  
300 scattered depending on the material molecular density. The production of X-ray energy is done by  
301 applying a very high voltage in a vacuum tube, and the detection is typically done by a charge  
302 collection device behind the material, which is connected to an electronic system to estimate the  
303 transmitted energy. Therefore, transmission X-ray (XRT) measures the variation in transmitted  
304 radiation through different materials and can be applied to detecting contaminated plastics or minerals  
305 (Firsching et al., 2013), and presence of metals (Knapp et al., 2014). Overlapping materials can be  
306 dealt with dual energy techniques (Li et al., 2016), but the less dense, smaller or thinner pieces of  
307 materials do not affect the x-ray radiation enough to produce a change in transmission. Fluorescence  
308 X-ray (XRF) is a technique to measure the fluorescent X-ray emitted after a material is excited with  
309 X-ray or gamma-ray radiation, and has been extensively investigated to detect preservative inorganic  
310 chemicals in waste wood from construction and demolition sources (Blassino et al., 2002; Block et al.,  
311 2007; Jacobi et al., 2007; Solo-Gabriele et al., 2004; Yasuda et al., 2006). The XRF methods were  
312 able to identify contaminated wood with a wide range of measurement time required per sample  
313 (0.25-6 seconds) (Rasem Hasan et al., 2011).

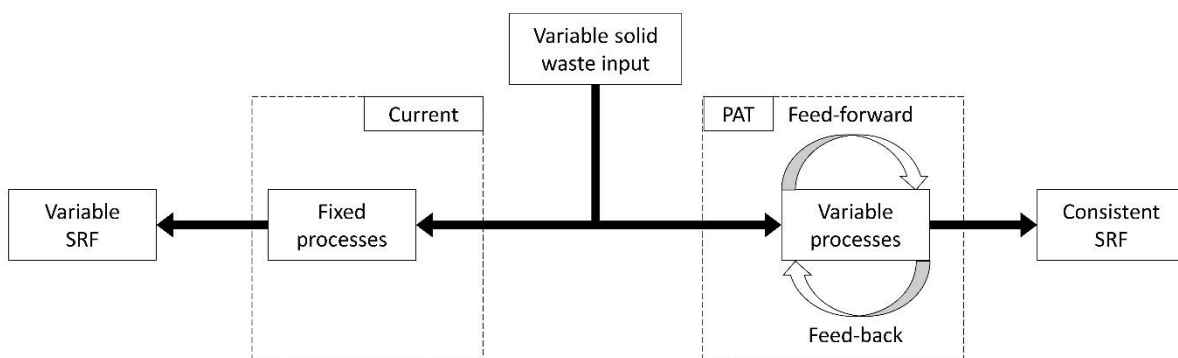
## 314 **3 PROCESS ANALYTICAL TECHNOLOGY**

315 Process analytical technology (PAT) is a framework designed to encourage innovation in  
316 manufacturing and quality assurance processes, originally introduced in 2004 by the FDA to the  
317 pharmaceutical industry in USA (FDA, 2004). The PAT guidance recommends the use of tools for

318 data acquisition, data and process analysis, and process control. Implementing PAT leads to the  
 319 understanding of production processes and being able to assess quality in real-time. Ever since the  
 320 introduction of PAT, the use of advanced technology in the pharmaceutical industry has increased  
 321 (Dickens, 2010; Simon et al., 2015) with multiple examples of successful implementations (Chen et  
 322 al., 2011; Mantanus et al., 2011; Reich, 2005; Rosas et al., 2012; Wu et al., 2011).

323 Process analysis concepts and tools are transferable (Simon et al., 2015), and activities other than  
 324 pharmaceutical have adopted the PAT approach, including the production of biofuels (Chadwick et  
 325 al., 2014), biotechnology (Gomes et al., 2015), food production (Tajammal Munir et al., 2015; Troy et  
 326 al., 2016; van den Berg et al., 2013), and manufacturing of catalysts (Wu et al., 2016). In all these  
 327 examples, the production plants are managed using PAT tools to collect key process information to  
 328 feed-back or feed-forward a central control system, improving the quality of the product in real-time.

329 The existing CEN/TC 343 standards only regulate SRF quality but make no recommendations  
 330 regarding waste processes or how to achieve the required quality. Emerging technologies applicable  
 331 to solid waste management systems (Gundupalli et al., 2016; Hannan et al., 2015; Lu et al., 2013)  
 332 could make it possible to apply PAT for the production of SRF. Similar to other industries, the  
 333 implementation of PAT could increase the understanding of the waste processes involved, allowing  
 334 for better control and quality monitoring and providing a consistent product, as illustrated in Figure 2.



335

336 **Figure 2.** Current waste management strategy (left branch), receiving waste of variable  
 337 content cannot control the product. The implementation of PAT (right branch) could allow  
 338 the waste processing plants to produce a consistent product.

339

### 340 3.1 CRITICAL QUALITY ATTRIBUTES

341 In a PAT framework, critical quality attributes are measurable characteristics that determine and  
342 indicate the quality of the product (FDA, 2009). In the case of solid waste management, these  
343 indicators would be the factors affecting the performance of the MBT processes identified in Table 1.  
344 Additionally, for the case of a MRF producing SRF, the main quality indicators required by EU  
345 standards (British Standards Institution, 2011d) would also be measured. Finally, adverse conditions  
346 affecting advanced sensors should also be considered, such as dirtiness, deterioration or degradation  
347 of material surfaces, or presence of dust and vapour in the air, some of which originate prior to the  
348 waste material arriving at the processing plants, whilst others are the result of the MBT operations  
349 during the treatment process. These properties are currently difficult to measure and quantify. Effects  
350 from the MBT processes could potentially be estimated, thus they currently represent a limitation and  
351 thus a challenge to the full implementation of PAT in the waste management industry. Therefore,  
352 further studies regarding their effects are needed.

353 The following section reviews the available advanced sensor technologies that could be used to  
354 measure each of the identified critical quality indicators. The performances of these technologies and  
355 methodologies are reported through (recognition and separation) rate values (%), coefficient of  
356 determination ( $R^2$ ) and determination errors (%). However, most studies using discriminant analysis  
357 report the Root Mean Square Error (RMSE), the range error ratio (RER) and the ratio of predictive  
358 deviation (RPD), which are dimensionless statistical values to compare different models and their  
359 performances. Therefore, a qualitative performance rating scale of poor, fair, good, very good, and  
360 excellent was adopted (Malley et al., 2002, 2004; Nduwamungu et al., 2009; Williams, 2001;  
361 Williams et al., 2006), enabling the comparison of published performance results of different  
362 technologies and methodologies, as shown in Table 2.

363 **Table 2.** Performance rating scale using the different commonly published performance  
364 parameters (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams  
365 et al., 2006), where  $R^2$  is the coefficient of determination, RPD is the ratio of the standard  
366 deviation of the original data to standard error of prediction, RER is the ratio of the range of  
367 the original data to standard error of prediction, % error is the percent error between the



368 predicted and the original data, and % rate is the success rate (recognition, classification,  
 369 separation, etc.) of the method.

Qualitative rating	Performance parameters				
	R <sup>2</sup>	RPD	RER	% error	% rate
poor	<0.70	<2.5	<9	>30	<70
fair	0.70 to 0.80	2.5 to 3.0	9 to 12	20 to 30	70 to 80
good	0.80 to 0.90	3.0 to 3.5	12 to 15	10 to 20	80 to 90
very good	0.90 to 0.95	3.5 to 4.0	15 to 18	5 to 10	90 to 95
excellent	>0.95	>4.0	>18	<5	>95

370

### 371 3.1.1 Problematic objects

372 The presence of objects and materials containing hazardous substances such as batteries, compressed  
 373 canisters or gas cylinders poses a health and safety risk to waste treatment plants and increases  
 374 environmental contamination (European Commission, 2015). Furthermore, certain types of materials  
 375 can affect the performance of some MBT processes, as a high percentage of hard materials or large  
 376 pieces can damage bag splitting and shredding equipment, whilst ductile materials can reduce the  
 377 performance of screening devices (Fitzgerald and Themelis, 2009; Tchobanoglous and Kreith, 2002).

378 Optical technologies have been used to identify and detect the presence of certain objects and  
 379 materials, based on visible features such as shapes and colours, resulting in good, very good and  
 380 excellent qualitative ratings (Table 3.). These algorithms were developed to find specific objects in  
 381 real time for industrial applications and no universal methodology has been developed. One identified  
 382 problem is the detection of black or very dark objects, in particular plastics, which absorb the light  
 383 and reduce their classification rates by 75%.

384 **Table 3.** Technologies and methods applied to problematic objects recognition. Performance  
 385 rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al.,  
 386 2006): \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
Optical VIS-nir-swir	Mixed cans and	Identifies aluminium cans and plastic bottles using a webcam and imaging	**** rate=91%	Yani and Budiman (2015)

	bottles	algorithms using visible shape features.		
<b>Optical VIS-nir-swir</b>	Mixed papers	Classifies paper based on quality grades using a webcam and different imaging algorithms using visible surface features.	**** rate>90%	Rahman et al. (2015, 2014, 2012b, 2012a, 2012c, 2011, 2010, 2009a, 2009b)
<b>Optical VIS-nir-swir</b>	Mixed plastic	Machine vision system using visible images to separate PET from non-PET plastic bottles based on shape and colour.	*** rate=80-95%	Wahab et al. (2006)
<b>Optical VIS-nir-swir</b>	Mixed plastic containers	Classifies Polycoat containers based on visible 3D geometrical characteristics.	***** error<4%	Mattone et al. (2000)
<b>Optical VIS-nir-swir</b>	MSW (inorganic)	Classifies non-ferrous metals, plastic bottles and coins using visible 3D features.	**** rate=91-99% (dark objects=20%)	Huang et al. (2010)
<b>Optical VIS-nir-swir</b>	MSW (inorganic)	Uses a webcam and image processing to classify plastic cutlery, plastic bottles, and aluminium cans based on shape.	***** rate=98%	Torres-García et al. (2015)

387

### 388 3.1.2 Particle size distribution

389 The size of the materials following shredding affects the performance of screening devices, ballistic  
390 separators, eddy current separators, and anaerobic digestion (Table 1). Particle size distribution (PSD)  
391 is also an important quality indicator of SRF, and the use of image analysis for large materials and  
392 objects is recommended by existing standards (British Standards Institution, 2012). Optical  
393 technologies using visible images and computer vision algorithms have been investigated for the  
394 determination of PSD in C&D waste, in all cases with fair to very good qualitative ratings based on  
395 their accuracy rates (Table 4).

396 **Table 4.** Sensor technologies and methods to estimate particle size distribution. Performance  
397 rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al.,  
398 2006): \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

<b>Technology</b>	<b>Target</b>	<b>Methodology</b>	<b>Performance</b>	<b>Author</b>
<b>Optical VIS-nir-swir</b>	C&D waste	Imaging algorithms and regression analysis to estimate PSD from sands and rocks.	** - **** rate=72-93%	Bianconi et al. (2015)
<b>Optical VIS-nir-swir</b>	C&D waste	Imaging algorithms to estimate PSD from recognizable features and a lookup table.	*** - ***** rate=82-95%	Di Maria et al. (2016)
<b>Optical VIS-nir-swir</b>	C&D waste	Imaging algorithms to estimate PSD from sand samples.	*** - ***** rate=86-91%	Urbanski et al. (2011)
<b>Optical VIS-nir-swir</b>	C&D waste	Imaging algorithms and regression analysis to estimate	** - *** rate=79-85%	Salehizadeh and Sadeghi (2010)

		PSD from sands and rocks.		
<b>Optical VIS-nir-swir</b>	MSW, ash	Image analysis to estimate PSD.	n/a	Nakamura et al. (2005)
<b>Optical VIS-nir-swir</b>	RDF	Machine vision to estimate PSD.	n/a	Immonen (2015)
<b>Optical VIS-nir-swir</b>	SRF	Image analysis to estimate PSD.	n/a	Dunnu et al. (2006)

399

400

### 401 3.1.3 Calorific value

402 The calorific value an important quality attribute of the produced SRF as it indicates the amount of  
403 recoverable energy from waste. Optical technologies have been applied to the determination of gross  
404 calorific value (GCV) with fair to excellent results. The indirect determination of GCV based on  
405 composition analysis using visible images reached excellent qualitative ratings, matching the best  
406 results obtained by more complex systems using visible and infrared hyperspectral analysis (**Error!**  
407 **Reference source not found.**). Spectral analysis reveals that a visible to SWIR spectrum (400-  
408 2500 nm) achieves good qualitative ratings, but limiting the bandwidth to NIR and SWIR regions  
409 (880-2500 nm) improves the estimates with excellent qualitative ratings. However, those studies  
410 which ignored the visible spectrum and were also part of the SWIR regions, obtained only fair or  
411 good qualitative ratings, which would indicate that the 1720-2500 nm region of the SWIR spectrum  
412 can reveal uniquely important information about GCV.

413 **Table 5.** Sensor technologies for the determination of calorific value. Performance rating  
414 (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 2006):  
415 \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
<b>Optical VIS-nir-swir</b>	MSW	Estimates GCV from visible image analysis of composition. Requires material database and human intervention.	***** R <sup>2</sup> =0.99	Wagland et al. (2013)
<b>Optical VIS-NIR- swir (450-950 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	***** R <sup>2</sup> =0.97,RER=16.7	Everard et al. (2012b)
<b>Optical VIS-NIR-</b>	biomass	Hyperspectral imaging with PLS regression analysis on straw	**** R <sup>2</sup> =0.89,RER=15.2	Huang et al. (2008a)

<b>SWIR (400-2498 nm)</b>		samples.		
<b>Optical VIS-NIR- SWIR (400-2500 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	*** R <sup>2</sup> =0.85,RER=13.4 RPD=2.56	Huang et al. (2008b)
<b>Optical vis-NIR- SWIR (880-1680 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	***** R <sup>2</sup> =0.97,RER=16.7	Everard et al. (2012b)
<b>Optical vis-NIR- SWIR (1100-2500 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	***** R <sup>2</sup> =0.99,RER=39.9 RPD=70.8	Fagan et al. (2011)
<b>Optical vis-NIR- SWIR (880-1720 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on energy crops pellet samples.	** R <sup>2</sup> =0.73,RER=3.1 RPD=1.0	Gillespie et al. (2015)
<b>Optical vis-NIR- SWIR (780-2498 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	**** RER=16.5	Lestander and Rhén (2005)
<b>Optical vis-NIR- SWIR</b>	SRF	Industry sponsored project. Indirect determination from composition analysis.	***** error<5%	Krämer and Flamme (2015)
<b>Optical vis-nir- SWIR (1400-2400 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	*** RER=14.0	Lestander and Rhén (2005)

416

#### 417 **3.1.4 Ash content**

418 The content of ashes is an important quality attribute of the produced SRF as it reduces the amount of  
419 recoverable energy from waste and places a burden on the management of residues. Optical  
420 technologies using hyperspectral image analysis have been applied to the determination of ash  
421 contents in biomass with poor to excellent qualitative ratings. Studies obtained excellent qualitative  
422 ratings using the complete NIR and SWIR regions, compared to methods limited to visible and NIR  
423 regions producing poor qualitative ratings (

424 **Table 6).** This may indicate that visible or NIR regions do not contain enough information regarding  
425 ash contents and a broader spectral analysis is required. Moreover, two studies using both NIR-SWIR  
426 region produced only fair qualitative ratings, which may be due to ignoring relevant parts of the NIR  
427 region (700-1000 nm) and SWIR region (1720-2500 nm). However, one case study was limited to  
428 only part of NIR and SWIR (1400-2400 nm) and still obtained excellent qualitative ratings when  
429 analysing woody samples, which implies that different materials may require specific spectrums.

430

431 **Table 6.** Sensor technologies for the determination of ash contents. Performance rating  
 432 (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 2006):  
 433 \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

<b>Technology</b>	<b>Target</b>	<b>Methodology</b>	<b>Performance</b>	<b>Author</b>
<b>Optical VIS-NIR-swir (450-950 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	* R <sup>2</sup> =0.52,RER=6.7 RPD=1.4	Everard et al. (2012a)
<b>Optical VIS-NIR-SWIR (400-2500 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	**** R <sup>2</sup> =0.93,RER=20.1 RPD=5.0	Huang et al. (2008b)
<b>Optical VIS-NIR-SWIR (350-2500 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	***** R <sup>2</sup> =0.99,RER=10.5	Labbé et al. (2008)
<b>Optical vis-NIR-swir (750-1100 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	* R <sup>2</sup> =0.58,RER=7.7 RPD=3.6	Fagan et al. (2011)
<b>Optical vis-NIR-SWIR (780-2498 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	***** RER=25.9	Lestander and Rhén (2005)
<b>Optical vis-NIR-SWIR (880-1720 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on energy crops pellet samples.	** R <sup>2</sup> =0.75,RER=6.6 RPD=1.8	Gillespie et al. (2015)
<b>Optical vis-NIR-SWIR (1000-2500 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	** R <sup>2</sup> =0.86,RER=1.2	Jin and Chen (2007)
<b>Optical vis-NIR-SWIR (1400-2400 nm)</b>	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	***** RER=20.9	Lestander and Rhén (2005)
<b>Optical vis-NIR-SWIR</b>	SRF	Industry sponsored project. Indirect determination from composition analysis.	**** error<10%	Krämer and Flamme (2015)

434

435

436 **3.1.5 Moisture**

437 The content of moisture can affect the performance of air separation, ballistic separation, magnetic  
438 separation, eddy current, and biodrying processes. It is also an important fuel quality indicator of SRF,  
439 as it determines the net calorific value of the material(British Standards Institution, 2011c). Different  
440 real-time technologies have been investigated to determine moisture in different materials, including  
441 capacitive and resistive, microwave and optical sensors. Capacitive sensors produced a range of poor  
442 to excellent qualitative ratings, with the best cases obtained when tested on MSW samples (

443 **Table 7).** Microwave sensors obtained fair to excellent qualitative ratings, with frequencies ranging  
444 from 9 to 26 GHz when testing on either biomass or MSW samples. The use of a resistive sensor was  
445 investigated but found the method limited to cases with 35% moisture or more.

446 Optical technologies were also investigated to estimate moisture in biomass and waste samples, with  
447 qualitative ratings ranging from poor to excellent. Hyperspectral analysis resulted in good to excellent  
448 qualitative ratings, and the frequency band seems to be affected by the studied material (



449 **Table 7).** Investigations on moisture in biomass, wood and bioenergy crops such as Miscanthus,  
450 using different spectrum regions (visible, NIR, SWIR) all resulted in excellent qualitative ratings. One  
451 case limited the method to multispectral analysis of 3 bands in the SWIR region (1740-2145 nm) and  
452 obtained excellent qualitative ratings with pharmaceutical pellet samples. This also implies that the  
453 choice of frequencies is influenced by the sampled material. Hyperspectral studies performed on rice  
454 straw samples obtained only fair qualitative ratings when limited to NIR and SWIR (1000-2500 nm),  
455 but very good qualitative ratings when including visible wavelengths (400-2500 nm).

456

457 **Table 7.** Sensor technologies for the determination of moisture contents. Performance rating  
 458 (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 2006):  
 459 \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
Capacitive	biomass	Compares 4 sensors on 98 types of wood and grass samples.	* - **** R <sup>2</sup> =0.31-0.94	Jensen et al. (Jensen et al., 2006)
Capacitive	MSW	Unaffected by flow rate, presence of metals or saline contamination.	***** R <sup>2</sup> =0.96 error<3.5%	Fuchs et al.(2008)
Microwave	biomass	Uses 9GHz and 12GHz sensors and linear regression analysis on wood sawdust samples.	** - **** RMSE=9.0-22.8%	Zhang and Ogura (Zhang and Ogura, 2010)
Microwave	biomass	Uses a 10GHz sensor and linear regression analysis on peanut hull pellets samples	***** R <sup>2</sup> =0.97,RER=19.3	Trabelsi et al. (Trabelsi et al., 2013)
Microwave	concrete and masonry	Sensor embedded in solid walls, using 2.2 to 2.7 GHz signals, not tested on loose materials.	***** error<1%	Sokoll and Jacob (2007)
Microwave	MSW	Sensor tested at 5, 16, and 26 GHz. Cannot detect thin water layers (<0.05mm).	**** Error=3-17%	Wagland et al.(2013)
Optical VIS-NIR-SWIR (400-2500 nm)	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	**** R <sup>2</sup> =0.93,RER=19.6 RPD=3.37	Huang et al. (2008b)
Optical VIS-NIR-swir (450-950 nm)	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	***** R <sup>2</sup> =0.96,RER=16.0 RPD=4.9	Everard et al. (2012a)
Optical vis-NIR-SWIR (780-2498 nm)	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	***** RER=57.1	Lestander and Rhén (2005)
Optical vis-NIR-SWIR (880-1720 nm)	biomass	Hyperspectral imaging with PLS regression analysis on energy crops pellet samples.	*** R <sup>2</sup> =0.88,RER=18.1 RPD=4.26	Gillespie et al. (2015)
Optical vis-NIR-SWIR (950-1664 nm)	food	Hyperspectral imaging with PLS regression analysis on coffee, soybeans and wafers samples.	***** - ***** R <sup>2</sup> =0.95-0.99 RMSEP=0.1-0.3	Achata et al.(2013)
Optical vis-NIR-SWIR (1000-2500 nm)	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	*** R <sup>2</sup> =0.89,RER=5.5	Jin and Chen (2007)
Optical vis-NIR-SWIR (1100-2500 nm)	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	***** R <sup>2</sup> =0.99,RER=39.3 RPD=13.5	Fagan et al. (2011)
Optical vis-NIR-SWIR (1400-2400 nm)	biomass	Hyperspectral imaging with PLS regression analysis on wood samples.	***** RER=51.4	Lestander and Rhén (2005)
Optical vis-NIR-SWIR	SRF	Industry sponsored project.	***** error<5%	Krämer and Flamme (2015)
Optical vis-NIR-SWIR	MSW	Industry sponsored project.	**** error<6%	Wünsch and Jenkins (2013)
Optical vis-nir-SWIR (1740-2145 nm)	pharma. pellets	Multispectral imaging and linear regression analysis using 3 bands.	***** R <sup>2</sup> =0.98	Rantanen et al.(1998)
Resistive	MSW	Limited to solid medium with moisture levels > 35%.	n/a	Gawande et al. (2003)

460

### 461 **3.1.6 Composition**

462 Knowledge of the variable composition of a mixed waste stream could affect the performance of  
463 manual separation, biodrying and anaerobic digestion processes, whilst being an important  
464 consideration towards the fuel quality of SRF. Different technologies have been investigated to  
465 identify materials in specific mixed waste streams. Hydrophobicity methods mechanisms for mixed  
466 plastics achieved good qualitative ratings, but they involve submerging the materials in a wet  
467 medium, the same with one case study using an ultrasound sensor (Table 8). Fluorescence, ultrasound  
468 and stiffness sensors can be utilised to separate mixed papers, with excellent qualitative ratings in the  
469 case of fluorescence but only when limited to papers printed without coloured inks. Similarly,  
470 identifying gold ore from mineral waste with X-ray technology resulted in good qualitative ratings.  
471 Good to excellent qualitative ratings were obtained using LIBS and PLS-DA analysis for quick  
472 classification of mixed metal alloys.

473 Optical technologies were also applied to determine composition of mixed waste material, including  
474 C&D and MSW. The results are affected by the studied material and the spectral region and image  
475 processing algorithms applied. For example, one case obtained good qualitative ratings classifying  
476 metals but another one provided excellent qualitative ratings of the full composition of C&D waste  
477 materials, and both used only visible imaging (Table 8). Hyperspectral analysis of WEEE using NIR  
478 and SWIR spectrum (1100-2100 nm) produced good qualitative ratings in identifying plastic  
479 contaminants, but another case obtained excellent qualitative ratings when extending the spectrum to  
480 include visible and NIR wavelengths (348-1008 nm) to identify the metal composition.

481 Good to very good qualitative ratings were achieved when estimating the composition of mixed waste  
482 using visible images of the waste materials, which indicates that the information in visible wavelength  
483 is enough to determine material composition. Multispectral analysis of NIR and SWIR images (1100-  
484 2500 nm) to identify plastics in MSW produced good qualitative ratings, which were improved upon  
485 when limiting the spectrum to SWIR (1548-2550 nm), obtaining excellent qualitative ratings. This  
486 implies that the NIR region may obscure the information in the SWIR region about the presence of  
487 plastics. Experiments with MIR and LIR regions of the spectrum (2500-25000 nm) resulted in good

488 qualitative ratings based on the identification rates of types of wastes, and excellent qualitative ratings  
 489 when identifying types of plastics without being affected by their colours.

490 **Table 8.** Sensor technologies for composition analysis of mixed materials. Performance  
 491 rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al.,  
 492 2006): \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good), \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
<b>Fluorescence</b>	Mixed papers	Measures fluorescence of lignin to separate 5 grades of paper. It is affected by colour inks.	***** rate=100%	Ramasubramanian et al. (2005)
<b>Hydrophobicity</b>	Mixed plastics	Review of flotation mechanisms to separate PVC or PET.	**** rates=60-100%, purities=70-100%	Wang et al. (2015)
<b>LIBS</b> <b>VIS-nir-swir</b> <b>(242-548nm)</b>	Mixed metal alloys	Classification of 10 types of metals at a 25 measurements per second rate.	***  Average rate>88%	Merk (2015)
<b>Optical VIS-nir-swir</b>	MSW	Full composition through image analysis. Requires material database and human intervention.	**** R <sup>2</sup> =0.91	Wagland et al. (2012)
<b>Optical VIS-nir-swir</b>	SRF	Full composition with image analysis. Requires material database and human intervention.	*** R <sup>2</sup> =0.89	Peddireddy et al. (2015)
<b>Optical VIS-nir-swir</b>	Mixed metals	Identifies stainless steel, brass and copper using visible imaging based on colour.	*** rate=80%	Kutilla et al. (2005)
<b>Optical VIS-nir-swir</b>	Mixed plastics	Uses imaging and histogram-based algorithms to classify PET and Polycoat containers.	***** rate=94-98%	Nawrocky et al. (2010)
<b>Optical VIS-NIR-swir</b>	Mixed textiles	Review of commercial devices to identify textiles.	**** rate>90%	Ishfaq (2015)
<b>Optical VIS-NIR-swir (384-1008 nm)</b>	WEEE	Hyperspectral image analysis to identify 6 non-ferrous metals.	***** rate=98%	Picon et al. (2009)
<b>Optical vis-NIR-SWIR (900-2500 nm)</b>	Mixed plastics	Hyperspectral imaging analysis to separates PET from bio-plastics.	n/a	Hollstein and Wohllebe (2015)
<b>Optical vis-NIR-SWIR (1100-2100 nm)</b>	WEEE	Hyperspectral image analysis to identifies plastics.	*** rate=80%, purity=70-80%	Beigbeder et al. (2013)
<b>Optical vis-NIR-SWIR (1100-2550 nm)</b>	MSW	Multispectral imaging analysis (6 bands) to identify plastics.	*** rate>80%	Wienke et al. (1996)
<b>Optical vis-NIR-SWIR</b>	SRF	Industry sponsored project. Full composition analysis, requires material database.	n/a	Krämer and Flamme (2015)
<b>Optical vis-nir-SWIR (1548-2550 nm)</b>	MSW	Multispectral imaging analysis (6 bands) to identify plastics.	***** rate>95% error<1%	van den Broek et al. (1996)
<b>Optical vis-nir-swir-MIR-LIR (2500-16667 nm)</b>	MSW, compost, landfill	Hyperspectral imaging analysis to identify 6 types of plastics, including black ones.	***** rate=100% (blacks=100%)	Kassouf et al. (2014)

<b>Optical vis-nir-swir-MIR-LIR (2500-25000 nm)</b>	MSW, compost, landfill	Hyperspectral imaging analysis to classify waste into 3 groups.	** rate=71%	Smidt et al. (2008)
<b>Stiffness</b>	Mixed papers	Separates 3 grades of paper. It can confuse a single sheet of paper with cardboard.	n/a	Ramasubramanian et al. (2007, 2006)
<b>Ultrasound</b>	MSW	Identifies and removes paper materials. Combined with an optical sensor.	**** rate=90%, purity=100%	Faibish et al. (1997)
<b>Ultrasound</b>	MSW	Identifies polymers in a wet medium.	n/a	Sanaee and Bakker (2009)
<b>X-ray</b>	Minerals	Uses XRT to detect gold ore.	*** rate=84%	Knapp et al. (2014)

493

494 **3.1.7 Biogenic carbon and biochemical methane potential**

495 The contents of biogenic carbon are an important fuel qualifier as it determines the potential fraction  
496 of renewable energy in SRF, and under relevant schemes could result in financial incentives (WRAP,  
497 2012b). Biochemical methane potential (BMP) is a related measure which estimates the maximum  
498 amount of biogas to be produced by anaerobic digestion processes. Optical methods have been  
499 investigated to measure both of these parameters, with poor to excellent qualitative ratings (

500 **Table 9).** The analysis of biomass samples using hyperspectral imaging in the NIR-SWIR range  
501 (1000-2500 nm) produced good qualitative ratings, but another experiment on rice straw samples  
502 which included the visible range (400-2500 nm) produced poor qualitative ratings. This might  
503 indicate that specific ranges are required for different samples, or that the visible range has to be  
504 ignored. Another case study with biomass samples but more limited spectral range (880-1720 nm)  
505 also produced poor qualitative ratings, which may indicate that the end of the SWIR range is required.  
506 However, a simple method using visible images and human interaction to determine composition and  
507 indirectly estimate biogenic fraction produced the best results with very good qualitative ratings.

508

509 **Table 9.** Sensor technologies for the determination of biogenic carbon contents and  
 510 determination of BMP. Performance rating (Malley et al., 2004, 2002; Nduwamungu et al.,  
 511 2009; Williams, 2001; Williams et al., 2006): \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very  
 512 good), \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
Optical VIS-nir-swir	MSW	Estimates biogenic fraction from visible image analysis of composition. Requires material database and human intervention.	**** error=5%	Wagland et al. (2013)
Optical VIS-NIR-SWIR (400-2500 nm)	biomass	Hyperspectral imaging with PLS regression analysis on rice straw samples.	* R <sup>2</sup> =0.67, RER=13.9 RPD=1.7	Huang et al. (2008b)
Optical vis-NIR-SWIR	MSW, others	Review of infrared methods to determine biochemical methane potential.	* - *** R <sup>2</sup> =0.26-0.88 RPD=1.49-2.88	Ward (2016)
Optical vis-NIR-SWIR (880-1720 nm)	biomass	Hyperspectral imaging with PLS regression analysis on energy crops pellet samples.	* R <sup>2</sup> =0.69, RER=6.6 RPD=1.8	Gillespie et al. (2015)
Optical vis-NIR-SWIR (1000-2500 nm)	MSW and others	Hyperspectral imaging with PLS regression analysis.	*** R <sup>2</sup> =0.85 RPD=1.8	Doublet et al. (2013)
Optical vis-NIR-SWIR (1100-2500 nm)	biomass	Hyperspectral imaging with PLS regression analysis on Miscanthus and short rotational coppice willow samples.	*** R <sup>2</sup> =0.88, RER=10.4 RPD=4.6	Fagan et al. (2011)

513

### 514 3.1.8 Contaminants

515 The detection of contaminants in the form of chemicals or unexpected materials is an important  
 516 indicator which determines the suitability of the waste streams and the fuel quality of the produced  
 517 SRF. Optical, X-ray and LIBS methodologies have been used to determine the presence of particular  
 518 contaminants. For example, when determining chemical preservatives in wood samples, X-ray  
 519 produced very good to excellent qualitative ratings, and optical hyperspectral analysis in the NIR and  
 520 SWIR range (1162-2197 nm) produced excellent qualitative ratings (

521 **Table 10).** With the sample application, LIBS produced better results when analysing plasma in a  
522 narrow band in the visible spectrum (330-510 nm) than when including at both visible and NIR (200-  
523 800 nm). The presence of particular chemicals in samples, such as chlorine and strontium, were  
524 determined with LIBS and analysis of visible spectra, both with excellent qualitative ratings.

525



526 **Table 10.** Sensor technologies for the identification of specific contaminants in mixed  
 527 materials. Performance rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009;  
 528 Williams, 2001; Williams et al., 2006): \* (poor), \*\* (fair), \*\*\* (good), \*\*\*\* (very good),  
 529 \*\*\*\*\* (excellent).

Technology	Target	Methodology	Performance	Author
<b>LIBS VIS-nir-swir (400-461nm)</b>	Mixed glass, soil	Detects presence of Strontium.	***** detection limit = 16-30ppm	Barefield et al. (1995)
<b>LIBS VIS-nir-swir (330-510 nm)</b>	Mixed wood	Detects presence of treated wood by identifying Chromium-based contaminants.	**** - ***** rate=92-100%	Moskal and Hahn (2002)
<b>LIBS VIS-nir-swir (330-510 nm)</b>	Mixed wood	Detects presence of treated wood by detecting Chromium-based contaminants.	***** rate=98-100%	Solo-Gabriele et al. (2004)
<b>LIBS VIS-NIR-swir (200-800 nm)</b>	Mixed wood	Detects chemical-based preservatives.	*** - **** R <sup>2</sup> =0.77-0.94	Martin et al. (2005)
<b>LIBS vis-NIR-swir (837.6 nm)</b>	C&I waste	Detects presence of chlorine in polymers.	***** detection limit = 18% (w/w)	Huber et al. (2014)
<b>Optical vis-nir-SWIR- MIR (2280-4480 nm)</b>	Mixed glass	Hyperspectral imaging and regression analysis to identifies ceramic glass contaminants.	**** rate=92-98%	Serranti et al. (2006)
<b>Optical vis-NIR-SWIR (1162-2197 nm).</b>	Mixed wood	Identifies chemical preservatives and 4 types of wood plastic composites.	***** rate=97-99%	Mauruschat et al. (2015)
<b>Optical vis-NIR-SWIR</b>	SRF	Industry sponsored project. Estimates chlorine contents based on composition analysis. It requires material database.	*** error<20%	Krämer and Flamme (2015)
<b>X-ray</b>	Mixed plastics	Uses dual energy XRT to detect presence of brominated flame retardants in polymers.	n/a	Firsching et al. (2013)
<b>X-ray</b>	Mixed wood	Detects presence of treated wood by using XRF to detect inorganic preservatives.	**** rate=85-100%	Rasem Hasan et al. (2011)
<b>X-ray</b>	Mixed wood	Detects presence of treated wood by using XRF to detect Arsenic-based contaminants.	***** rate=100%	Solo-Gabriele et al. (2004)

530

### 531 **3.2 PROCESS MONITORING TOOLS**

532 Eight quality indicators have been identified in the scope of a MRF, which would determine the fuel  
 533 quality of the produced SRF. Selecting the best tools for each of these indicators shows that optical  
 534 technologies can be applied to measuring all of them (Table 11). Optical methods using visible light  
 535 cameras combined with computer vision algorithms could measure five of the eight indicators, and the  
 536 rest would require infrared spectral imaging and mathematical analysis. The visible image processing  
 537 algorithms would need to be tested waste processing on industrial scale, in particular with dark or

538 black objects, which present a problem to spectral imaging analysis. Alternatively, capacitive and  
 539 microwaves sensors could be used to determine moisture contents, and LIBS could detect and  
 540 quantify some contaminants. The presence of chlorine contaminants in waste materials has been  
 541 investigated but further research is required to monitor presence of mercury and heavy metals in  
 542 mixed solid waste.

543 **Table 11.** Best available technologies for each indicator when applied to waste materials.

Indicator	Technologies	Notes
<b>Problematic objects</b>	Optical (visible)	Different algorithms needed depending on location in the process. More tests needed on mixed waste.
<b>Particle size distribution</b>	Optical (visible)	Different algorithms needed depending on location in the process. More tests needed on mixed waste.
<b>Calorific value</b>	Optical (visible)	Needs algorithm development of automatic material recognition on mixed waste. Indirect determination needs database of material properties.
	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects. Indirect determination needs database of material properties. Direct determination method needs testing on MSW.
<b>Ash contents</b>	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects.
<b>Moisture</b>	Capacitive	Need testing with MSW in industrial scale.
	Microwave	Need testing with MSW in industrial scale.
	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects.
<b>Composition</b>	Optical (visible)	Automated method on subset of C&D waste. MSW method needs algorithm development of automatic material recognition. Indirect determination needs database of material properties.
	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects.
<b>Biogenic carbon and BMP</b>	Optical (visible)	Needs algorithm development of automatic material recognition on mixed waste. Indirect determination needs database of material properties.
<b>Contaminants</b>	LIBS	Identifies PVC, but quantification of Chlorine contents not in real-time. Can detect preservatives in wood samples.
	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects. Indirect estimate of Chlorine based on PVC fraction requires database of material properties.

544

545 When applied to a MRF, every mechanical and biological process could make use of critical data  
 546 measured by optical technology using visible sensors (

547 **Table 12**), with some of them requiring extra information which could be provided by either infrared  
548 spectroscopy, capacitive or resistive sensors. Problematic objects recognition technologies could offer  
549 information regarding presence of hazardous materials, which could trigger an automatic stop of the  
550 plant processes until the dangerous item is removed. Multiple object recognition sensors could be  
551 deployed in one single plant, in particular before each shredder, looking for specific items, sizes and  
552 shapes, according to their position in the process. The identified contaminants or unsafe objects could  
553 be sent through alternate treatment routes to be processed as required, reducing risks and potential  
554 fines.

555 Particle size distribution sensors could be deployed together with moisture and composition analysis  
556 sensors before any stage using separation based on physical properties, such as screening, air and  
557 ballistic separators. Gaining real-time information of moisture, composition and PSD could improve  
558 the separation processes which would adjust their operational parameters accordingly. Particle size  
559 distribution data is required by European standards to inform stakeholders about the quality of solid  
560 waste streams and waste derived fuels.

561 Calorific value, ash contents and moisture sensors could be installed at different stages of MRF,  
562 allowing the processes to route and possibly mix waste streams of different composition to obtain the  
563 desired WDF quality. Mixing wastes with different measured properties, for example a stream with  
564 low CV with a stream of high CV could allow an operator to produce the required WDF with the  
565 highest possible efficiency by controlling the mix fractions in real-time. Early detection of  
566 contaminants such as chlorine could be used to prevent them from going into WDF, recycling or  
567 landfill, enabling better material recovery and reducing environmental pollution.

568

569 **Table 12.** Critical quality indicators and the available monitoring tools for the different waste  
 570 process units.

Process	Critical quality indicators	Available monitoring tools
<b>Bag splitting</b>	Problematic objects - Presence of large or hard items in the input stream	Optical (visible)
<b>Shredding</b>	Problematic objects - Presence of large or hard items in the input stream	Optical (visible)
<b>Screening</b>	Problematic objects - Presence of highly ductile material which end up in fines fraction	Optical (visible)
	Particle size distribution (PSD)	Optical (visible)
<b>Air separation</b>	Moisture	Optical (infrared hyperspectral) Capacitive Microwave
	Particle size distribution (PSD)	Optical (visible)
<b>Ballistic separation</b>	Moisture	Optical (infrared hyperspectral) Capacitive Microwave
	Particle size distribution (PSD)	Optical (visible)
<b>Magnetic separation</b>	Particle size distribution (PSD)	Optical (visible)
	Moisture	Optical (infrared hyperspectral) Capacitive Microwave
<b>Eddy current separation</b>	Particle size distribution (PSD)	Optical (visible)
	Moisture	Optical (infrared hyperspectral) Capacitive Microwave
	Composition - presence of aggregated materials	Optical (visible) Optical (infrared hyperspectral)
<b>Biodrying</b>	Moisture	Optical (infrared hyperspectral) Capacitive Microwave
	Composition - presence of aggregated materials and organic material	Optical (visible) Optical (infrared hyperspectral)
	Particle size distribution (PSD)	Optical (visible)
<b>Anaerobic digestion</b>	Composition - organic material	Optical (visible) Optical (infrared hyperspectral)
	Biochemical methane potential (BMP)	Optical (visible)

571

572 Significantly, current techniques are designed and implemented for, typically, a single application (i.e.

573 detection of specific plastic types or removal of metals). Each technology works in isolation, with

574 little system-level data sharing, validation, and reconciliation. Therefore, no single technology or

575 system provides the operator with all the parameters required, thus further opportunities exist in

576 developing technologies capable of informing and impacting material recovery and fuel production in

577 real time.

578 **4 CONCLUSIONS AND PERSPECTIVES**

579 Waste management services currently present a situation similar to that of the pharmaceutical industry  
580 over a decade ago, whereby quality was assessed by collecting samples and then assessed using  
581 laboratory testing. Existing technology could be used to improve waste derived fuel production  
582 processes, by developing better real-time analysis and control tools for material recovery facilities.

583 This article answers two key questions:

584 A. which information, or critical quality attributes, would need to be collected for the  
585 implementation of PAT in the waste management industry; and

586 B. which sensor technologies, or process monitoring tools, could provide this information in  
587 real-time to improve waste material treatment processes.

588 Each of the waste processes used in MRFs could benefit from implementing PAT and gaining  
589 information about the waste stream. Using real-time quality measurements to adjust the operational  
590 parameters of MBT processes could lead to a consistently improved quality of waste derived fuel.  
591 This in turn reduces uncertainty due to fluctuations from input waste streams, increases the energy  
592 and material recovered and reduces landfill waste disposal.

593 Optical technologies, in particular those using visible sensors, offer the most flexibility as they can be  
594 used to measure most of the critical quality indicators. Some attributes such as the presence of  
595 mercury and other heavy metals, are still not developed for mixed solid materials and could represent  
596 a challenge. However, indirect determination of fuel quality properties based on composition analysis  
597 and a database of material properties database offer a viable alternative, as they produce similar or  
598 better results than direct determination analysis. Near-infrared spectrographic analysis technologies  
599 are limited by working distances, particle sizes, and the presence of undetectable materials such as  
600 dark objects, metals, and glass, which do not necessarily affect visible-sensor methods. Another  
601 potential challenge for both NIR spectroscopy and visible camera methods are the effects of dirtiness  
602 and the degradation of material surfaces, which could cause false-positive results.

603 The integration of existing applicable technologies, used so far in isolation or for very specific  
604 reasons, in the framework of process analytical technologies to provide real-time waste information  
605 could improve the overall efficiency of the waste treatment industry. The generated waste data could  
606 also provide needed information to stakeholders, such as governments, local authorities, regulators  
607 and waste industry operators, for better decision-making in the future.

608

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