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

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

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

1 INTRODUCTION

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

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

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

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

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

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

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

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

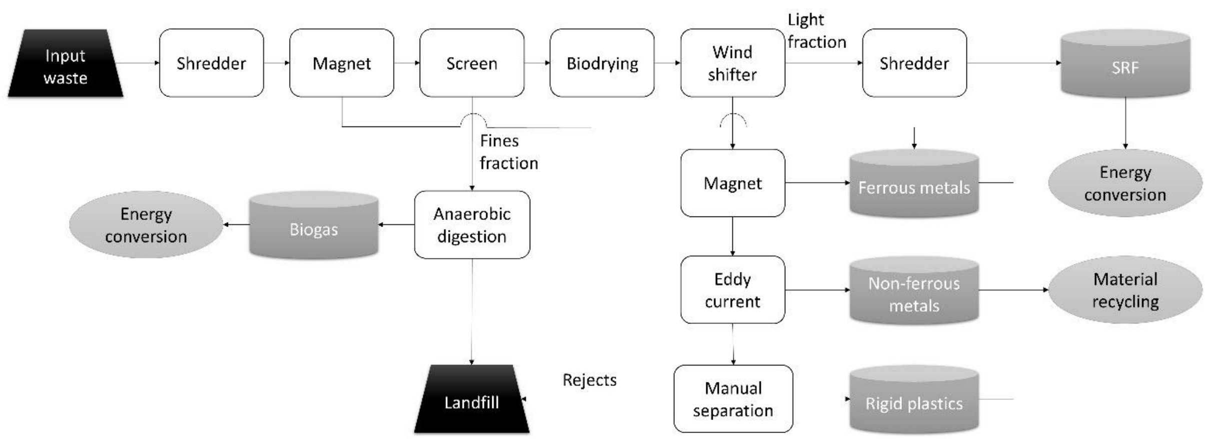

Figure 1. Flow sheet diagram of a typical MRF using manual and MBT processes to produce four outputs: biogas and SRF for energy conversion, materials for recycling, and rejects going into landfill. Adapted from DEFRA *(2013)*.

1.1 MANUAL SORTING

Hand picking or manual sorting is a physical operation performed by plant personnel working in special facilities installed at different waste processing stages. The goal is to either sort the waste items based on material type, or to remove those items that could reduce the performance of other processes downstream (Tchobanoglous and Kreith, 2002). Humans have a unique ability to recognise materials in a very short time (Sharan et al., 2014), with observed waste recovery efficiencies up to 95% (Tchobanoglous and Kreith, 2002). Many factors affect this efficiency, such as fatigue, circulation speed, particle size distribution and volumetric flow of the waste material, and environmental aspects such as working temperature and lighting. The overall manual sorting efficiency is proportional to the number of people performing these tasks, but also requiring larger facilities.

1.2 BIOLOGICAL PROCESSES

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

1.3 MECHANICAL PROCESSES

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

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

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

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

2 ADVANCED SENSORS

These new types of automated processes use combinations of advanced, non-invasive sensors and mechanical processes to provide fast separation and sorting of materials. Usually, the sensor is used to detect a particular characteristic of a material, classifying it and deciding its destination fraction using a computer system, and then a mechanical process separates it from the mixed stream accordingly (Velis et al., 2010). Advanced online processes are fundamental to reliably sort materials, increasing the waste processing plant efficiency by producing high purity recycled and SRF materials(WRAP, 2010).

2.1 FLUORESCENCE

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

2.2 HYDROPHOBICITY

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

2.3 LASER INDUCED BREAKDOWN SPECTROSCOPY

Laser induced breakdown spectroscopy (LIBS) involves focussing a high energy laser onto a material which generates plasma emissions with a particular light spectrum. These emissions are detected with a spectrograph and analysed to determine the material chemical composition, such as contaminants. For example, Barefield et al. (1995) used this technique to detect the presence of Strontium in mixed waste. Similarly, the presence of contaminated waste wood can be detected with LIBS, with measurement times of 3-5 seconds per sample (Rasem Hasan et al., 2011). A comprehensive list of detection limits obtained for different chemicals has been published by Zorov et al. (2015). Huber et al. (2014) investigated the use of LIBS to detect chlorine in industrial waste in real-time, without being affected by the visible colour of the plastics.

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

2.4 MICROWAVES

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

2.5 RESISTIVITY AND CAPACITY

This group of sensors can detect changes in electrical fields due to variations of pressure, humidity, and conductivity. They range from very simple to complex circuitry designs that allow for increased functionality, such as self-calibration and error compensation. In general, they are low cost, small sized and with low power consumption (Du, 2014). Resistive sensors measure changes in resistivity between two electrodes when in the presence of conductor media such as water. A proposed method (Gawande et al., 2003) calibrated a resistive sensor using mixed solid waste. Capacitive sensors measure the dielectric permittivity of materials between two plates (Udo and Christof, 2010). The method investigated by Fuchs et al. (2008) measures moisture content in municipal solid waste falling off a conveyor belt with a capacitive sensor.

2.6 STIFFNESS

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

2.7 ULTRASOUND IMAGING

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

2.8 OPTICAL IMAGING USING VISIBLE WAVELENGTH SENSORS

Visible optical sensors are based on the surface properties of materials to reflect varying intensities of light in wavelengths visible to the human eye (400-700 nm). Visible image sensors, such as complementary metal-oxide semiconductor (CMOS) and charged couple devices (CCD) cameras, produce images with pixel intensities proportional to the visible light received (Janesick, 2007). Unique features in the materials and the generated images, such as shape, colour and surface textures can be used to recognize objects, for example bottles (Nawrocky et al., 2010; Torres-García et al., 2015; Wahab et al., 2006), cans (Torres-García et al., 2015; Yani and Budiman, 2015), minerals (Anding et al., 2011, 2013), and electronic boards (Kleber et al., 2015; Torres-García et al., 2015). Optical imaging has also been studied to determine particle size distributions of different mixed materials (Bianconi et al., 2015; Nakamura et al., 2005; Salehizadeh and Sadeghi, 2010; Urbanski et al., 2011). Typical issues affecting these visible optical imaging methods are changes in illumination, or the presence of different materials or objects presenting similar visible features such as colour.

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

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

2.9 OPTICAL IMAGING USING INFRARED WAVELENGTH SENSORS

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

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

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

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

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

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

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

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

2.10 X-RAY IMAGING

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

3 PROCESS ANALYTICAL TECHNOLOGY

Process analytical technology (PAT) is a framework designed to encourage innovation in manufacturing and quality assurance processes, originally introduced in 2004 by the FDA to the pharmaceutical industry in USA (FDA, 2004). The PAT guidance recommends the use of tools for data acquisition, data and process analysis, and process control. Implementing PAT leads to the understanding of production processes and being able to assess quality in real-time. Ever since the introduction of PAT, the use of advanced technology in the pharmaceutical industry has increased (Dickens, 2010; Simon et al., 2015) with multiple examples of successful implementations (Chen et al., 2011; Mantanus et al., 2011; Reich, 2005; Rosas et al., 2012; Wu et al., 2011).

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

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

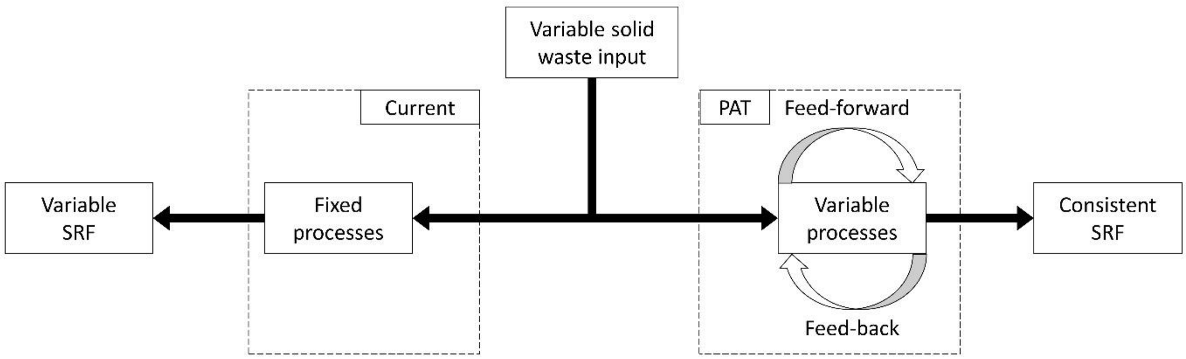

Figure 2. Current waste management strategy (left branch), receiving waste of variable content cannot control the product. The implementation of PAT (right branch) could allow the waste processing plants to produce a consistent product.

3.1 Critical quality attributes

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

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

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

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

Qualitative rating	Performance parameters				
	R^2	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

3.1.1 Problematic objects

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

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

Table 3. Technologies and methods applied to problematic objects recognition. Performance rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 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.		
Optical VIS-nir-swir	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)
Optical VIS-nir-swir	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)
Optical VIS-nir-swir	Mixed plastic containers	Classifies Polycoat containers based on visible 3D geometrical characteristics.	***** error<4%	Mattone et al. (2000)
Optical VIS-nir-swir	MSW (inorganic)	Classifies non-ferrous metals, plastic bottles and coins using visible 3D features.	**** rate=91-99% (dark objects=20%)	Huang et al. (2010)
Optical VIS-nir-swir	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)

3.1.2 Particle size distribution

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

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

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

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

3.1.3 Calorific value

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

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

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

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

3.1.4 Ash content

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

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

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

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

3.1.5 Moisture

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

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

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

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

Table 7. Sensor technologies for the determination of moisture contents. Performance rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 2006): * (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^2 =0.31-0.94	Jensen et al. (Jensen et al., 2006)
Capacitive	MSW	Unaffected by flow rate, presence of metals or saline contamination.	***** R^2 =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^2 =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^2=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^2 =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^2=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^2=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^2 =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^2=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^2 =0.98	Rantanen et al.(1998)
Resistive	MSW	Limited to solid medium with moisture levels > 35%.	n/a	Gawande et al. (2003)

3.1.6 Composition

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

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

Good to very good qualitative ratings were achieved when estimating the composition of mixed waste using visible images of the waste materials, which indicates that the information in visible wavelength is enough to determine material composition. Multispectral analysis of NIR and SWIR images (1100-2500 nm) to identify plastics in MSW produced good qualitative ratings, which were improved upon when limiting the spectrum to SWIR (1548-2550 nm), obtaining excellent qualitative ratings. This implies that the NIR region may obscure the information in the SWIR region about the presence of plastics. Experiments with MIR and LIR regions of the spectrum (2500-25000 nm) resulted in good qualitative ratings based on the identification rates of types of wastes, and excellent qualitative ratings when identifying types of plastics without being affected by their colours.

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

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

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

3.1.7 Biogenic carbon and biochemical methane potential

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

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

Table 9. Sensor technologies for the determination of biogenic carbon contents and determination of BMP. Performance rating (Malley et al., 2004, 2002; Nduwamungu et al., 2009; Williams, 2001; Williams et al., 2006): * (poor), ** (fair), *** (good), **** (very 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^2=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^2 =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^2=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^2=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^2=0.88, RER=10.4 RPD=4.6	Fagan et al. (2011)

3.1.8 Contaminants

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

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

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

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

3.2 PROCESS MONITORING TOOLS

Eight quality indicators have been identified in the scope of a MRF, which would determine the fuel quality of the produced SRF. Selecting the best tools for each of these indicators shows that optical technologies can be applied to measuring all of them (Table **11**). Optical methods using visible light cameras combined with computer vision algorithms could measure five of the eight indicators, and the rest would require infrared spectral imaging and mathematical analysis. The visible image processing algorithms would need to be tested waste processing on industrial scale, in particular with dark or black objects, which present a problem to spectral imaging analysis. Alternatively, capacitive and microwaves sensors could be used to determine moisture contents, and LIBS could detect and quantify some contaminants. The presence of chlorine contaminants in waste materials has been investigated but further research is required to monitor presence of mercury and heavy metals in mixed solid waste.

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

Indicator	Technologies	Notes
Problematic objects	Optical (visible)	Different algorithms needed depending on location in the process. More tests needed on mixed waste.
Particle size distribution	Optical (visible)	Different algorithms needed depending on location in the process. More tests needed on mixed waste.
Calorific value	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.
Ash contents	Optical hyperspectral (800-2500 nm)	Cannot measure black/dark objects.
Moisture	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.
Composition	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.
Biogenic carbon and BMP	Optical (visible)	Needs algorithm development of automatic material recognition on mixed waste. Indirect determination needs database of material properties.
Contaminants	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.

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

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

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

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

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

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

Significantly, current techniques are designed and implemented for, typically, a single application (i.e. detection of specific plastic types or removal of metals). Each technology works in isolation, with little system-level data sharing, validation, and reconciliation. Therefore, no single technology or system provides the operator with all the parameters required, thus further opportunities exist in developing technologies capable of informing and impacting material recovery and fuel production in real time.

4 CONCLUSIONS AND PERSPECTIVES

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

This article answers two key questions:

A. which information, or critical quality attributes, would need to be collected for the implementation of PAT in the waste management industry; and
B. which sensor technologies, or process monitoring tools, could provide this information in real-time to improve waste material treatment processes.

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

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

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

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