The application of image recognition methods to improve the performance of waste-to-energy plants

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Abstract: In this paper, we present an image recognition method to improve the performance of waste-to-energy plants. Thermal treatment of waste in waste-to-energy plants is central for the treatment of municipal solid waste. The heterogeneous nature of municipal solid waste results in a fluctuating lower calorific value to which plant operation must be adapted. Compensating for drastic changes in the lower calorific value is challenging for plant operation and can require short-term interventions. Estimating the lower calorific value prior to the combustion process should reduce the number of short-term interventions. In this work, we propose a process-engineering approach to estimate the lower calorific value of waste as a new application of image recognition in waste-to-energy plants. The method is implemented using videos and sensor data from a case study in a real waste-to-energy plant in Germany.

Keywords: waste-to-energy; image recognition; waste properties; process modeling

Addresses Sustainable Development Goal 9: Industry, innovation and infrastructure

1. Introduction

Waste-to-energy (WtE) is the process which uses residual materials as primary energy to generate electricity and/or heat. The key to understand its importance is that it mainly concerns municipal solid waste (MSW), i. e. trash from cities. MSW comes from households, commerce, trade, office buildings, small institutions, garden and street sweepings, among others. The utilization of MSW is not trivial. Ideally, in a circular economy, the amount of recycled material should be maximized and residual waste minimized. Even in an ideal scenario, residual waste could never be completely eliminated. Therefore, policies exist which aim to regulate the utilization. If this is not done adequately, the impacts to human health and environment are harmful. Just to set one example, MSW decomposition in landfills produces methane, which, according to the IPCC (Intern-governmental Panel on Climate Change), has a global warming potential 28

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times higher than CO_2 [UN16]. For this reason, waste generation and recycling is one of the 231 indicators for monitoring the United Nations' sustainability strategy [DeS20].

The amount of MSW generated is strongly driven by population and urbanization. The problem is that, on the one hand, more people produce more trash and, on the other hand, waste production per capita has increased significantly. From the year 2010 to 2015, annual production of garbage in China, Thailand, Vietnam, India and Pakistan combined grew from 60 Mt to over 300 Mt. It is also estimated that it could more than double during 2015-2025, resulting in over 600 Mt of MSW annually by 2023 [IE19].

As a consequence of the growth, new waste management solutions need to be implemented. Using WtE plants has become essential to provide two solutions: waste treatment and clean energy supply [MH20]. In Germany, WtE plants are well developed offering a very high environmental standard. Current digital technologies have an immense potential to further optimize the performance of the plants, and support the decision-making of the operators.

Artificial intelligence (AI) is widely implemented for waste applications such as waste production forecasting and waste management or classification. Waste classification is used when individual objects can be identified. Ruiz et al. and Chu et al. both present methods using image recognition combined with deep learning to automatically detect objects in waste for recycling [Ch18; Ru19]. Image processing has also been used, but mostly using spectral analysis. In 2013, Vijayakumar et al. implemented infrared spectral analysis to classify the 15 different types of PET bottles [VR13]. Bonifazi et al. used similar methods to propose a fast classification strategy [Bo22]. This, however, cannot be applied in WtE plants since MSW is completely mixed and objects generally cannot be detected.

In addition, machine learning (ML) models have great potential for predicting the thermal properties of waste. Taki et al. used four different types of artificial neural networks (ANNs) to predict the higher heating value of MSW based on the initial materials [TR22]. Genuino et al. used ANNs to investigate the extraction of humic substances from waste during chemical activation [Ge17]. Yet, these studies are based on data sets which include characteristics of the waste, which cannot be identified for MSW in a WtE plant.

Our previously published work has focused on analyzing whether image recognition methods can be used to characterize waste as fuel for WtE plants, using different transfer learning methods and pre-trained datasets [Pe21]. Additionally, ML methods have been implemented to make operationally relevant predictions based on the historical sensor data [Pe22].

The scope of the present research is to introduce a self-developed image recognition method to identify parameters important for the characterization of waste as fuel for WtE plants. In this new approach, image processing is used to determine physical waste properties, and AI is applied to estimate the characteristics of the waste as fuel. In this way, a proactive component may be added to the combustion control process which will facilitate plant operation. This method's limitations are determined by the heterogeneity of the waste and its properties such as the lower calorific value (LCV), water content or porosity, which strongly influence the combustion process. To provide optimum combustion conditions, as much information as possible should be gained on these properties prior to combusting the waste. In the future, image recognition is to be used to analyze the waste as it is fed to the WtE plant to obtain such information. Such an AI model will only be able to predict the range in which the LCV varies. However, this is sufficient since for an optimized operation of the incinerator it is not the absolute values of the LCV but the changes in LCV that are of importance for the decision process and configuration of the combustion.

The presented method is implemented in a case study, which has been carried out in a WtE plant in Hannover, Germany. The plant is operated by EEW and treats approximately 280000 t MSW per year [EE22]. Fig. 1 shows a schematic overview of the plant. The plant uses forward acting grate firing technology. The waste is temporarily stored in a bunker, where it is mixed for homogenization. The operator uses a crane to charge MSW into a funnel, which then passes onto the grate through. Air is added through the grate for combustion. The hot flue gases from the combustion pass through a steam generator, where the heat is transfered to a water-steam-cycle. The resulting steam is used to generate electricity in a turbine and generator as well as for district heating in the city of Hannover. The gases receive a flue gas treatment, which ensures that all exhaust gases comply to the legally specified emission limits.

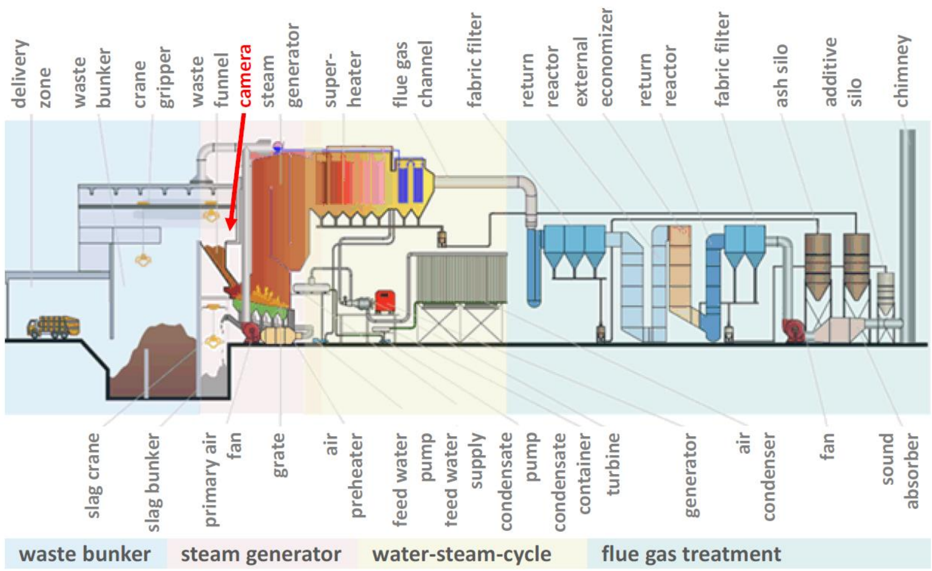


Fig. 1: Schematic layout of a waste-to-energy plant with forward acting grate firing technology [Cy21].

The paper is organized as follows: in section 2 the method developed to estimate physical waste properties with regard to the combustion process by using measurement data is presented. In section 3 the image processing method is shown. Section 4 combines sections 2 and 3, in order to describe how the data architecture of a holistic training set looks like. Finally, section 5 contains the discussion and conclusion.

2. Obtaining physical waste properties with regard to the combustion

Information on the varying waste properties during combustion are required to provide target information for image recognition. It is important that the images of the waste in the training dataset are accompanied by high quality waste property information to ensure the best possible result of the image recognition.

2.1 Lower calorific value

Waste is characterized by different properties. The most important property for combustion processes is the lower calorific value (LCV). It quantifies the energy released during combustion. LCV is a property which may be measured using calorimeters. Such an analysis, however, is unfeasible inside a full-scale WtE plant. Instead of calorimeters, energy balances across the steam generator of the WtE plant are used to derive LCV from measurements obtained inside the steam generator [Ho07]. Hence, the value of LCV is not measured directly but indirectly through temperature, pressure, concentration and mass flow rate measurements.

2.2 Residence time

Using measurements inside the steam generator to derive properties of the waste requires knowledge of the time delay between waste feeding and combustion of the waste on the grate in the steam generator, i. e. the residence time of the waste. The residence time depends on the operating conditions. A varying time delay has to be considered therefore when matching images and measurements.

An experimental investigation of the waste residence times in the feeding system was conducted to obtain information on the time delay [Ga21]. Regression equations were derived which provide the basis to compute the current residence time based on operating parameters of the plant. To estimate for example the residence time in the funnel and chute Δt in min at time t, the velocity of the ram u_{ram} in mm/min may be used according to the equation

$$\widehat{\Delta t}(t) = 97.35 - 0.14 \int_{t}^{t+1h} u_{ram}(\tau)\, d\tau \tag{1}$$

The coefficient of determination R^2 of this regression is 0.32 with a root mean squared error (RMSE) of 8.25 min. The residence times obtained using eq. (1) are due to the comparatively large RMSE not suitable to predict exact values of Δt. However, they may be used to assess the trend of Δt.

Different approaches are possible to use the result of eq. (1) to match the waste images to the computed waste properties. Fig. 2 presents the experimentally obtained residence times with three different methods for residence times quantification.

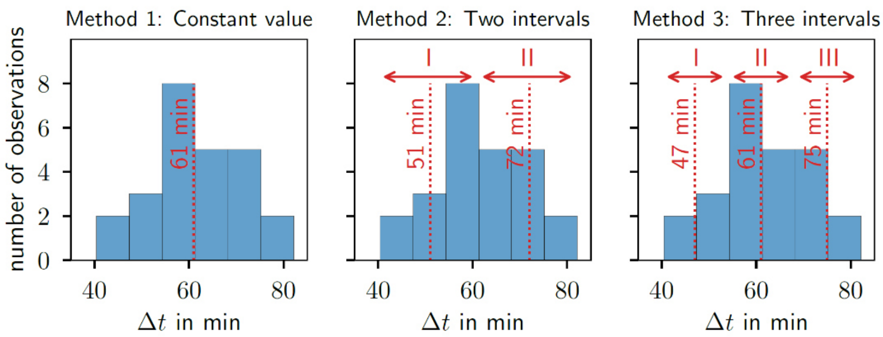


Fig. 2: Different options to assess the residence time.

The first method uses a constant value for Δt. The mean value of all measured residence times, 61 min, is a suitable value. The second method divides the measured residence times into two intervals I and II. Depending on $\widehat{\Delta t}$ computed using eq. (1), the value of Δt is set to either 51 min or 72 min according to

$$\widehat{\Delta t} \leq 61 \rightarrow \Delta t = 51 \text{ min} \qquad \text{(interval I)} \tag{2a}$$

$$\widehat{\Delta t} > 61 \rightarrow \Delta t = 72 \text{ min} \qquad \text{(interval II)} \tag{2b}$$

The third method in Fig. 2 defines three intervals I, II and II. The value of Δt is set to 47 min, 61 min, or 75 min depending on Δt based on

$$\widehat{\Delta t} \leq 54 \rightarrow \Delta t = 47 \text{ min} \qquad \text{(interval I)} \tag{3a}$$

$$54 \leq \widehat{\Delta t} \leq 68 \rightarrow \Delta t = 61 \text{ min} \qquad \text{(interval II)} \tag{3b}$$

$$\widehat{\Delta t} > 68 \rightarrow \Delta t = 75 \text{ min} \qquad \text{(interval III).} \tag{3c}$$

The most suitable method to match images and waste properties has to be selected in an iterative process. It is expected that the chosen method will vary depending on the examined aspect.

3. Obtaining physical waste properties during waste feeding using

image processing

In general, all power plants operate on the same operation principle: generating electricity from a source of primary energy. In the case of WtE plants, the fuel used is waste produced by the citizens. The characterization of the fuel in a power plant, i. e. knowledge of the physical properties of the fuel, is crucial for the power generation. In contrast to other power plants, WtE plants handle a very heterogeneous fuel. While a continuous chemical analysis of the waste could provide detailed information about the material composition in the waste, such a method is not practical at all for in-plant applications. Instead, image analysis is used to gain valuable information about the waste before it is combusted.

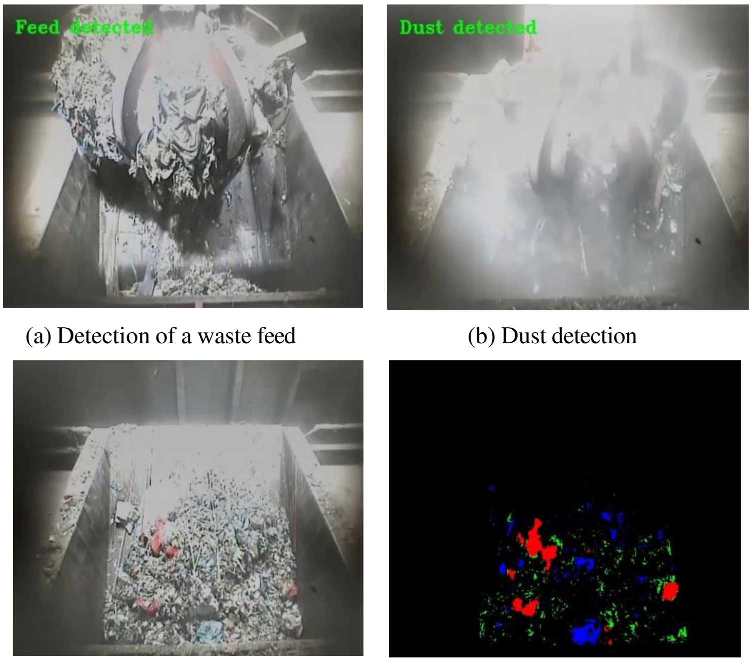
3.1 Camera system

The choice of the cameras is an important aspect in the development of the new technology. Technologies such as multispectral imaging would allow to specify the chemical composition of single objects. This type of technologies are successfully used in applications, where the waste is organized and close to the camera [Bo22; TR22], a scenario not given in a WtE plant. In addition, the waste must be illuminated properly to apply multispectral imaging. Due to safety concerns regarding the flammability of the waste, this requirement cannot be met in the waste bunker. RGB cameras are therefore used to monitor the MSW at the funnel. These cameras are not a hazard and do not affect the plant operation. The location of the camera system in the plant is indicated in Fig. 1.

3.2 Analyze waste feeding

With the camera system installed, it is neither possible to identify individual waste components nor to determine the overall composition of the components, except in a few special cases, e. g. feeds containing large objects such as mattresses or barriers, among others. Yet, experienced crane operators can use visually obtained information to estimate the potential LCV of a feed. Using their expert knowledge, it was possible to identify several physical properties related to the feeds that can be extracted using image processing. These properties include the weight, color, feed duration and properties related to water content.

In general, the procedure of waste feeding can be divided into several phases. In the first phase, the crane operator grabs waste from the waste bunker using the crane gripper and navigates the waste-filled gripper to the funnel. The crane scale can be used to determine the weight of the currently grabbed waste. When the gripper is positioned over the funnel, it is opened and the waste is released. Dust may occur during this second phase. According to the experienced operators, dust formation is an indicator for the water content of the waste. Thus, the dust duration is determined using image processing. After the dust subsides, the waste becomes visible. In the third phase of the feed, the waste gradually slides into the waste chute. During this phase, more information about the physical properties of the current feed is extracted from the videos. By tracking structures detected in the waste, the movement of the waste can be monitored. In this way, the time it takes for the waste to slide into the chute, i. e. the feed duration, can be determined. In addition, the evolution of the velocity can be analyzed. The velocity at which the waste slides into the chute might provide useful information about the water content of the waste, i. e. moist waste might slide more quickly. At the same time, one must take into account that external circumstances such as the filling level of the chute also affect the velocity at which the waste slides. While the waste slides, representative images of the waste that characterize the feed are extracted. From these representative images, further physical properties to characterize the current feed can be determined. For example, the color of the waste can be analyzed. These properties combined represent the visual cues used by experienced operators to classify the waste as fuel and to estimate its LCV. The decision process of an experienced operator will therefore be simulated by extracting these properties using image processing. In Fig. 3, exemplary frames from a waste feed and the information gained by image processing are shown.



(a) Detection of a waste feed (b) Dust detection

(c) Exemplary representative (d) Color analysis of representative

Fig. 3: Exemplary frames from the videos recorded at the waste funnel. The top panels (a) and (b) show feed and dust detection, respectively. In the bottom panels (c) and (d), an exemplary representative image and the corresponding color analysis as extracted for each feed are shown.

4. Data architecture for image recognition

The methods presented in Section 2 and 3 should be implemented in the WtE plant case study in Hannover, Germany. As the project has not been completed, this is still work inprogress. Fig. 4 illustrates the data architecture that should be used for processing image and sensor data.

Due to the heterogeneity of waste, the LCV in WtE plants varies significantly over time. The WtE plant can operate within a certain range of LCVs. Yet, on the one hand, the lower heating value must be high enough for the waste to inflame, but on the other hand, it must not be so high that the thermal load on the plant's components exceeds the allowed limits. Moreover, compensation of unexpected drastic changes in the LCV is problematic as the effects of the fluctuating LCV must be compensated by intervening in the combustion control, e. g. by changing the combustion air supplied or by introducing auxiliary fuels (light heating oil). Finding relations between the information on the feed gained by the image processing and the calculated LCV would enable to estimate the LCV in the future. In this way, it could be possible to adjust the processing parameters in advanced and reduce the number of short-term interventions.

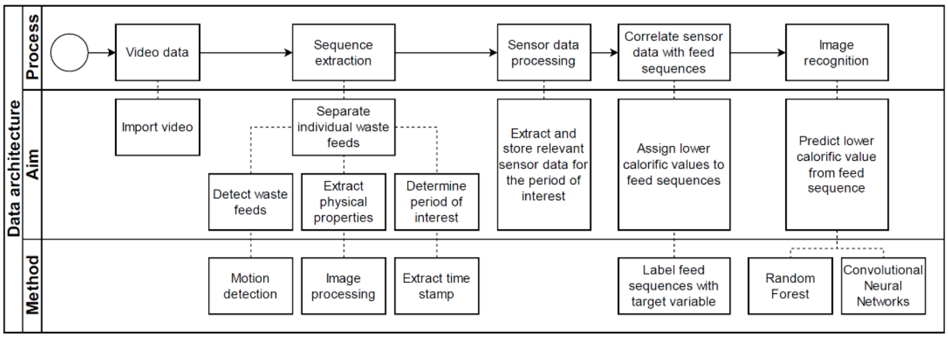


Fig. 4: Flow diagram illustrating the architecture used to relate information gained by image processing to the sensor data.

Within our new process-engineering approach, the information gained by image processing should be related to the LCV observed in the steam generator. Given a video sequence from the camera at the funnel, in a first step the feed sequences within the video are detected and separated from one another. Subsequently, image processing is performed to extract the information characterizing each feed, as described in Section 3. In order to extract the relevant sensor data for each feed, the operating parameters of the plant are analyzed and the residence time of each feed is determined by one of the quantification approaches presented in Section 2. The combustion process of the waste in the steam generator is a continuous process during which the energy of the waste is released. Hence, the LCV of each waste feed is stated as an average value across the combustion period. Accordingly, the sensor data needed to calculate the LCV is extracted from the plants operating parameters for the period of interest. In a next step, each feed sequence will be labeled with the average LCV as target variable. In this way, a training data set for image recognition will be generated. This data set can be used to train an AI model for predicting the LCV based on the information gained by image processing in the future.

5. Discussion and Conclusion

The presented work exhibits that image recognition of waste is a challenging problem. Waste is a very heterogeneous fuel and cannot be compared for example to coal. Nevertheless, WtE plants are an essential technology to handle the remains of developed societies. Image recognition at the waste funnel may provide a new tool to detect rapidly changing physical properties. Due to the mixed, unordered nature of the waste treated in the WtE plant, multispectral imaging, as known from applications such as waste recycling for analyzing the material composition of single objects, is not applicable for this purpose. However, a process-engineering approach that uses image processing to analyze the physical properties of the feeds can be applied to characterize the waste feeds. A challenge is to relate the properties obtained by image processing to the operating parameters of the WtE plant, since the residence time of the waste is not constant. Therefore, three different options for integrating the residence time into the model are proposed. In addition, the continuity of the combustion process in the steam generator further impedes the assignment of one LCV to each waste feed.

In this work, we presented a new process-engineering approach for integrating image recognition into WtE plant operation. The aim of this approach is to establish an AI model capable of estimating the LCV of the waste such that the number of short-term interventions in the plant operation can be reduced. In a next step, we will develop a demonstrator for applying the data architecture presented in this paper to the real operating WtE plant in Hannover. As the research is still ongoing, there are no final results available. The combination with physical properties and process flows might be an ideal support for the image recognition.

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Bibliography

[Bo22] Bonifazi, G.; Capobianco, G.; Cucuzza, P.; Serranti, S.; Uzzo, A.: Recycling- oriented characterization of PET waste stream by SWIR hyperspectral imaging and variable selection methods. Detritus/, pp. 42–49, Mar. 2022.

[Ch18] Chu, Y.; Huang, C.; Xie, X.; Tan, B.; Kamal, S.; Xiong, X.: Multilayer Hybrid Deep-

Learning Method for Waste Classification and Recycling. Computational Intelligence and Neuroscience 2018/, pp. 1–9, Nov. 2018.

[Cy21] Cyris, F.: Prozessgütemonitoring der Wärmekraftumwandlung von Abfallverbrennungskraftwerken. TEWISS-Technik und Wissen GmbH, 2021.

[DeS20] DeStatis Statistisches Bundesamt - Abfallaufkommen in Deutschland, visited on: 06/02/2020.

[EE22] EEW: Standorte Hannover, 2022, url: https://www.eew-energyfromwaste.com/de/standorte/hannover, visited on: 05/19/2022.

[Ga21] Garmatter, H.; Bauer, L.; Cyris, F.; Scharf, R.: Experimentelle Unter- suchung der Verweilzeit von Siedlungsabfällen im Abfalltrichter und auf dem Vorschubrost eines Abfallverbrennungskraftwerks. In (Beckmann, M.; Hur- tado, A., eds.): Kraftwerkstechnik 2021. SAXONIA Standortentwicklungs- und -verwaltungsgesellschaft mbH, Freiberg, pp. 71–82, 2021, isbn: 978-3-949169-01-4.

[Ge17] Genuino, D. A. D.; Bataller, B. G.; Capareda, S. C.; De Luna, M. D. G.: Appli- cation of artificial neural network in the modeling and optimization of humic acid extraction from municipal solid waste biochar. Journal of environmental chemical engineering 5/4, pp. 4101–4107, 2017, issn: 2213-3437.

[Ho07] Horeni, M.; Beckmann, M.; Fleischmann, H.; Barth, E.: Ermittlung von Betriebsparametern in Abfallverbrennungsanlagen als Voraussetzung für die weitere Optimierung. In (Thomé-Kozmiensky, K. J.; Beckmann, M., eds.): Energie aus Abfall Band 2. Neuruppin, 2007.

[IE19] IEA: Will energy from waste become the key form of bioenergy in Asia? In. Paris, 2019.

[MH20] Mohammadi, M.; Harjunkoski, I.: Performance analysis of waste-to-energy technologies for sustainable energy generation in integrated supply chains. Computers & Chemical Engineering 140/, 2020.

[Pe21] Pehlken, A.; Eschemann, P.; Garmatter, H.; Cyris, F.; Nieße, A.: Einsatz von Künstlicher Intelligenz in der Digitalisierung von Abfallverbrennungskraftwerken. INFORMATIK 2021/, 2021.

[Pe22] Pehlken, A.; Garmatter, H.; Dawel, L.; Cyris, F.; Beck, H.; Schwark, F.; Nieße, A.: How can machine learning improve waste-to-energy plant operation. In. 2022.

[Ru19] Ruiz-Parrado, V.; Sanchez, A.; Vélez, J.; Raducanu, B.: Automatic Image-Based Waste Classification. In. Pp. 422–431, May 2019, isbn: 978-981-10-4912-5.

[TR22] Taki, M.; Rohani, A.: Machine learning models for prediction the Higher Heating Value (HHV) of Municipal Solid Waste (MSW) for waste-to-energy evaluation. Case Studies in Thermal Engineering 31/, p. 101823, 2022, issn: 2214-157X.

[UN16] Intergovernmental Panel on Climate Change (IPCC), visited on: 2016.

[VR13] Vijayakumar, S.; RAJAKUMAR, P. R.: Infrared Spectral Analysis of Waste Pet Samples. International Letters of Chemistry, Physics and Astronomy 4/, pp. 58–65, Sept. 2013.