Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 128 (2024) 250–255

www.elsevier.com/locate/procedia

34th CIRP Design Conference

Modular Model and Simulation for Process Optimisation in Advanced Material Recovery Facilities (MRFs)

Milan Liu[a,*], Sue Grimes[b], Konstantinos Salonitis[a], Lampros Litos[a]

[a]*Sustainable Manufacturing Systems Centre, School of Aerospace, Transport and Manufacturing, Cranfield University, United Kingdom*
[b]*Environmental and Water Resource Engineering, Imperial College London, United Kingdom*

* Corresponding author. *E-mail address:* milan.liu@cranfield.ac.uk

Abstract

At a time when the supply of critical materials is threatened, waste recycling and reuse is an essential solution for human development. The role of Material Recovery Facilities (MRFs) to deliver efficiently high-purity material fractions as feedstock cannot be underestimated. However, MRF sorting processes need to remain adaptive with evolving smart technologies and systems that further enhance their effectiveness. For example, a re-designed MRF with AI-based robotics can improve the performance of waste recycling, leading to significant economic and environmental benefits. This study assesses the performance of potential optimisation methods for future proofing MRFs using modular simulation methods. The authors set out to review current robotics sorting technology and pointed out the challenge of efficiency analysis with multiple variables. The study develops a new conceptual model of efficiency analysis considering the identification and sorting limitations of robots, as well as the coordination requirements between robots and conveyor belts. A computational model is designed and developed by modularity program codes to help practitioners gain insight into the MRF performance by modifying the variables (composition of input waste, separation coefficients and configurations) and analysing the resulting assessment factors (purity and recovery). In the end, this study demonstrates the performance of the optimisation methods of MRF (two target materials for one robot and recirculation loops) through simulation.

© 2024 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 34th CIRP Design Conference

Keywords: Material recovery facilities; Recycling; Sorting; Optimisation; Modular program; Simulation

1. Introduction

One of the main challenges of current waste management is to increase waste recycling rates worldwide, whereas global waste generated annually is expected to increase from 2.59 billion tonnes in 2030 to 3.4 billion tonnes by 2050 [1]. Material Recovery Facilities (MRFs) implement a series of sophisticated processes to separate different waste streams effectively. Optimising the waste treatment processes to recover pure material fractions as feedstock can lead to the overall reduction in energy consumption, climate change mitigation and minimisation of environmental impacts. Therefore, the role of a Materials Recovery Facility designed and optimised to deliver efficiently high purity material fractions cannot be underestimated and helps to preserve natural resources and promote a circular economy.

Nomenclature

AI	Artificial Intelligence
MFA	Material Flow Analysis
MRF	Materials Recycling Facility
OS	Optical Sorter
SC	Separation Coefficient

To separate waste materials for recycling or discarding as appropriate, processing options include hand sorting, screening (size separation), magnetic field separating, shredding (size

2212-8271 © 2024 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 34th CIRP Design Conference
10.1016/j.procir.2024.07.050

reduction), optical sorting, etc [2]. The manual sorting activity can raise high personnel costs, sometimes accounting for nearly 60% of the total MRF operation cost [3] and can lead to potential risks of human fatigue and exposure to dangerous substances. The utilisation of integrated sensing technologies and robotic classification technology, therefore, can be an attractive cost-effective and efficient solution to overcome these challenges. This study focuses on the development of a methodology for sorting process efficiency when using advanced technologies in MRFs.

2. Literature review

2.1. AI-based robotic sorting systems and the influencing factors of sorting efficiency

Robotic sorting systems can efficiently handle various materials with quality, consistency, and flexibility, with the help of AI technology [4–6], which offers great optimisation opportunities for MRFs. Various sensors can distinguish unique characteristics of different material types based on their visual properties such as colour, shape, and texture [7]. Optical sorters (OSs) based on optical sensors primarily contribute to the binary classification of the waste stream, with the performance of up to more than 90% purity of recycled materials [8].

The data from the sensors can be used to build and test waste classification models through machine learning algorithms to implement AI-based vision sorting systems. The machine learning algorithms have significant benefits shown in sorting and separating recyclable materials, from accuracy to time savings [4,5,9–11]. Particularly, based on the integration of software and matching hardware, it can execute multitasking tasks if AI is deployed, making it feasible for a single robot to complete several sorting tasks simultaneously [12]. However, the performance of this configuration in real MRFs is unknown and difficult to prove so far.

There are many types of factors that affect sorting efficiency in the traditional MRFs. The key internal operating variables of the MRF can be regulated by the operators, which include waste input feed rate; conveyor belt speed, ballistic board slope, nozzle NIR pressure, etc. The external variables affecting the performance include the inlet waste composition and throughput, which can only be monitored [13]. The composition of the waste stream is dynamic and fluctuates throughout the day, making it challenging to describe and predict in numbers.

The sorting efficiency of vision-based AI robotic units is more complicated, which can be limited by their identification and sorting capability. The difficulty can arise from various environmental factors like lighting, as well as the waste itself, which can morph in shape and size [10]. Materials like plastic bottles can be compressed, and paperboard can be torn, without altering their inherent properties, making it challenging to identify them as intact objects. Particularly, when materials began to overlap, touch, and cover each other without forming a monolayer, the robot showed increasing difficulties in detecting and processing objects [14]. Robots must also consider the feasibility of grasp and manipulation according to the identified surface conditions, while robustly tracking moving objects [10,15].

2.2. Separation coefficients in MRF simulation

To characterise the separation efficiency of multiple waste material facilities, separation/transfer coefficients are utilised, usually defined as the ratio of any output stream to the sum of the input streams [16,17]. The values of these separation efficiencies for specific processes can be derived from expert judgment/equipment suppliers, experimental estimated data, or MFA-based modelling. For the model of Tanguay-Rioux et al. [18], transfer coefficients are calculated by averaging the mass flows obtained for the 200 iterations for the main unit operations. Furthermore, Tanguay-Rioux et al. [19] developed a new model with a combination of mechanistic modelling and efficiency transfer coefficients utilisation, which can calculate the output of different unit operations after introducing six properties as independent variables of the material stream, including bulk density, shape, moisture, etc.

Material Flow Analysis (MFA) is a useful systematic assessment of material flow within a spatially and temporally defined system [20]. The output can be calculated from the input stream using the law of conservation of mass, or the process can be performed in reverse. Testa introduced a network flow model with known separation parameters to predict the performance of whole MRFs [21]. Testa's model can simulate the output flow with the following input parameters: 1) waste input compositions, 2) sorting line configuration, and 3) separation efficiencies [16].

Facing the challenge of the flexibility and complexity of the configuration of MRFs, a modular model consisting of different modules (components) representing diverse units with unique functions is a desirable method. It can be reconfigured according to changes in the input material mix and provides simulations according to the needs of the user [22]. This also makes it feasible and convenient to integrate new advanced technologies and update the system. However, a review of the literature suggests there is no generic modelling methodology trying to estimate the efficiency of MRFs with AI-based robotic units, which may be affected by the limited identification and sorting capability of robotics units. In this case, building a modular model considering the important influencing factors like belt parameters and input waste properties is worth exploring as a potential option for the efficiency analysis of robotic sorting systems.

3. Methodology

In collaboration with a waste sorting robot manufacturer in the UK, the authors sought to model the sorting process with a mathematical modular model and simulate its performance in different system configurations. The model and simulation intend to demonstrate how to approach the complexity and integration problems identified in the literature review. The study is conducted in the following steps:

1. Modular model development. Firstly, the scope and the assessment factors of the model are identified to build a modular model focused on robotic sorting systems. The

main assessment factors include recovery rate and material purity. Secondly, a belt module is developed and integrated into the model. The inspiration for considering the belt parameters comes from the industrial experience shared by an expert from the company.

2. Simulation scenario design. The sorting lines in the target configurations consist of optical sorters and AI-based robots only. The optical sorters can separate various plastics via bursts of compressed air using optical technology [23]. The robot can be set at the end of the sorting line to enhance the waste sorting and concentrating process.
3. Coding of the model based on the mathematical relationships of set configurations. Every module and the general algorithm are built in Python as independent classes. Simulating MRFs in given configurations can be achieved by adjusting the operating factors of these modules and designing their sequence. In addition to designed configurations, other inputs include the input waste composition, operation conditions (belt width, belt speed, target materials for each unit) and system factors (maximum belt width, maximum belt speed, machine age of use, etc.), are changeable with an Excel interface. The output data include final waste composition, purity, and recovery. This method can simulate the fate of various materials in different configurations. Sankey diagrams are used as a suitable way to visualise mass flows.
4. Simulation and data analysis. All assumed the data as input for configuration 1 - 3 is unchanged. Monte Carlo simulation is used to test the performance of the automated control of the sorting system with the help of the feedback mechanism of the belt module.

4. Model development

4.1 Mathematical representation of the modular model

A series of performance factors are used to assess MRF processing commingled dry recyclables, such as recovery, purity (or grade) and overall throughput. The definitions of conventional factors and their mathematical symbols are introduced in Table 1 as per Velis et al., [24].

Table 1. Summary of symbols

Symbol	Description
m	Mass
u	A sorting operation unit
$P_{u,i}$	An output of the unit; i = 1, 2, 3, ⋯, n
$I_{u,j}$	An input of the unit; j = 1, 2, 3, ⋯, n
I_u	The overall input after collecting all the inputs
M_k	A type of material in the system; k = 1, 2, 3, ⋯, n
$C(\mathrm{M}_k)_{P_{u,i}}$	Purity of material M_k in the output $P_{u,i}$
$R(\mathrm{M}_k)_{P_{u,i}}$	Recovery of material M_k in the output $P_{u,i}$

The purity $C(\mathrm{M}_k)_{P_{u,i}}$ refers to the ratio of mass (m) of component M_k in the output $P_{u,i}$ over the total mass of this output, which can be defined as:

$$C(\mathrm{M}_k)_{P_{u,i}} = \frac{m(\mathrm{M}_k)_{P_{u,i}}}{m_{P_{u,i}}} \quad (1)$$

The recovery $R(\mathrm{M}_k)_{P_{u,i}}$ refers to the ratio of the mass (m) of component M_k in the output $P_{u,i}$ over the total mass of M_k from all input streams, which can be defined as:

$$R(\mathrm{M}_k)_{P_{u,i}} = \frac{m(\mathrm{M}_k)_{P_{u,i}}}{\sum_{j=1}^{n}(m_{I_{u,j}} \cdot C(\mathrm{M}_k)_{I_{u,j}})} = \frac{m(\mathrm{M}_k)_{P_{u,i}}}{m_{I_u} \cdot C(\mathrm{M}_k)_{I_u}} \quad (2)$$

$$\sum_{j=1}^{n}(m_{I_{u,j}} \cdot C(\mathrm{M}_k)_{I_{u,j}}) = \sum_{i=1}^{n}(m_{P_{u,i}} \cdot C(\mathrm{M}_k)_{p_{u,i}}) \quad (3)$$

The mass of different materials M_k (k = 1, 2, 3, ⋯, n) in output $P_{u,i}$ sorted out by unit u can be calculated by the corresponding separation coefficients (SCs). For example, for a unit with n inputs and m outputs in total, the material stream of M_k is shown in Fig. 1. All the materials can be calculated and tracked in this way once the SCs determined.

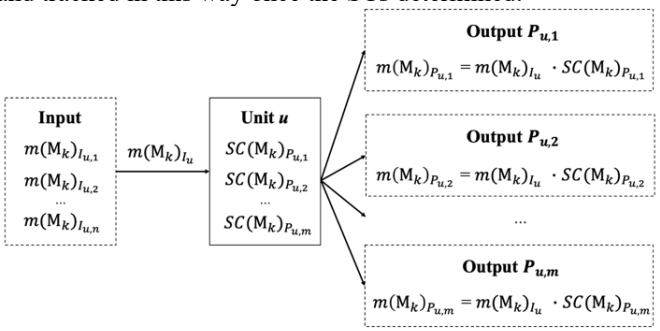

Fig. 1. Diagram of material streams of M_k with n inputs and m outputs for a sorting unit

4.2 Mathematical representation of the configurations

Multiple optical sorters (OSs) can be used and arranged sequentially to separate several target materials. Robots are placed on the final sorting line to purify the output streams and sort out target materials. The following 3 configurations are considered in this study:

1. In configuration 1 (config. 1), M_1 is the target material for the sorting line consisting of OS1 and following Robot 1 (R1), and similarly, M_2 is the target material for the sorting line consisting of OS2 and following Robot 2 (R2). M_1 and M_2 are expected to be sorted out and accumulate in the positive output $P_{R1,1}$ and $P_{R2,1}$ separately. SC(M_1) of $P_{R1,1}$ is greater than that of $P_{R1,2}$. SC(M_2) of $P_{R2,1}$ is greater than that of $P_{R2,2}$. Assessment factors include $R(\mathrm{M}_1)_{P_{R1,1}}$, $R(\mathrm{M}_2)_{P_{R2,1}}$ and $C(\mathrm{M}_1)_{P_{R1,1}}$, $C(\mathrm{M}_2)_{P_{R2,1}}$.
2. In configuration 2 (config. 2), assume that R1 can implement the sorting function of R2 at the same time, sorting out M_1 and M_2 into the positive output $P_{R1,1}$ and $P_{R1,2}$ respectively. The input of R1 is the sum of the $Pos_{1,1}$ and $Pos_{2,1}$:
$$m(\mathrm{M}_k)_{I_{R1}} = m(\mathrm{M}_k)_{P_{OS1,1}} + m(\mathrm{M}_k)_{P_{OS2,1}} \quad (4)$$
3. In configuration 3 (config. 3), a recirculation loop is added into the system aiming to integrate (part of) the output $P_{R1,3}$ into the input feed (Fig. 2). The material streams in the system will be updated as the input changes. Through the recirculation loop, valuable materials are directed back to the upstream sorting unit, providing another sorting opportunity for these target materials, and reducing the amount of residual waste deposed to landfill. The iteration of the loop has been applied to the algorithm of the simulation model to achieve the mass balance of recirculation loops. One negative output of any unit can

enter the upper stream, as part of the new input together and go through the sorting system again. The new input of the next iteration consists of the initial input and the negative output of the downstream unit. Consequently, there would be new material streams and outcomes for every unit. This iteration will be repeated until the value of output has an acceptable marginal gap compared to the previous output. In other words, the mass balance has been achieved in this steady-state model. The acceptable gap is assumed as 10^{-3} t/h in this study.

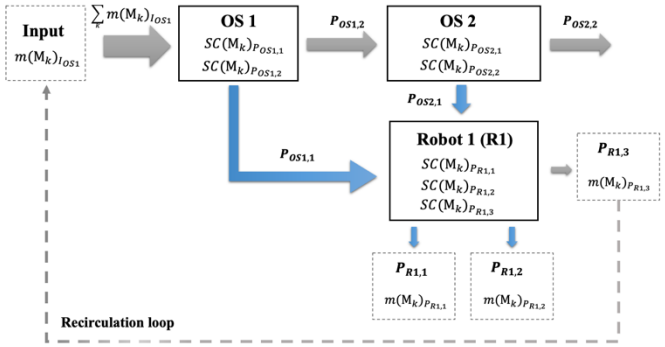

Fig. 2. Diagram of one robot sorting out two materials with a recirculation loop. The blue arrow denotes positive flow and the grey arrow denotes negative flow.

4.3 Conveyor Belt Module

The waste feed input (m) of a unit refers to the waste entering the unit through a conveyor belt, which should be equivalent to or below the throughput (m_{max}) – the total amount of waste that MRF currently accepts. For simplicity, it is assumed that there will be enough storage space for extra waste when overflowing. For conveyor belts, the common parameters are belt speed (v, m/min), belt width (d, m) and belt coverage rate (q, %). The belt coverage rate (q) refers to the ratio of the area of materials over the total area of the belt. It should be the function of the parameters mentioned above as shown in equation (5), where γ as a size factor for unit conversions.

$$q = \frac{m \cdot \gamma}{v \cdot d} \quad (5)$$

The belt coverage rate reflects the real spread level of materials. It determines how easily the sensor can target and recognise the material and how easily the robot can pick up the material, which corresponds to the identification and sorting ability of the unit, respectively. Overcrowded materials on the conveyor belt are obstructive to sensor recognition and robot pickup efficiency. An inefficient identification occurs when items are commingled, dirty and/or overlapped on the belt conveyor [13]. Thus, assume coverage rate (q) can determine the identification coefficient (α) as well as the sorting coefficient (β). These mathematics functions with the belt coverage as the variables can be explored by future experiments to be done. In this simulation research, the hypothesised mathematics relationship has been applied as shown in equation (6 - 8). Assume the final separation coefficient (SC) of this unit is presented as the product of these two coefficients. The age of the machines is also an influencing factor affecting efficiency.

$$\alpha = -0.232q^2 - 0.174q + (1.02 - age * 0.005) \quad (6)$$

$$\beta = -0.232q^2 - 0.264q + (1.02 - age * 0.005) \quad (7)$$

$$SC = \alpha \cdot \beta \quad (8)$$

Overall, with the above input variables of the belt module and initial input belt parameters, the key factor coverage rate (q) can be calculated, which can affect the identification coefficient (α) and sorting coefficient (β). In the end, the output of the belt module is the estimated overall separation coefficient (SC) of this unit.

The robotic sorting system can be more intelligent with an automation control of the belt module. After predicting overall SCs from the belt module, the coordination of units can be optimised by adjusting the coefficient to the idea range by controlling the belt speed or waste feed rate directly. This feedback mechanism can be built based on equation (5), assuming other inputs are fixed except belt speed (v), belt coverage rate (q) can be considered as the function of variable belt speed - $q(v)$. If the estimated q (v) calculated is beyond or below the ideal range at any time, the system is expected to adjust the v positively or negatively by a certain margin to obtain a new speed as a new input to the model for a final acceptable appropriate SC. Similarly, waste feed input (m) can be the only variable if other factors are fixed. The same feedback mechanism can be built.

5. Results and discussion

5.1 The performance of the optimised configurations

Configuration 1 (config. 1) consists of two OSs and two robots for two target materials. Suppose each optical sorter has its own target material and performs binary separation with a defined separation coefficient. The positive output, which contains most of the target material, will enter the further sorting process by the robot, while the remaining part will go to the next optical sorters. The mass flow charts of config.1 - 3 are shown in Fig. 3.

After combining $P_{R1,1}$ and $P_{R2,1}$ from OS1 and OS2 as a new input for Robot 1 (R1), the sorting unit R1 has two target materials M_1 and M_2. Separation coefficients are calculated by the belt module based on the current belt coverage rate of R1 (q = 41.42 %) according to the equation (5 - 8). Compared to the previous q_{R1} (29.86%) and q_{R2} (11.56%) in config. 1, the sharp growth of the belt coverage rate may be due to the additional material streams from OS2.

Compared config.1 to config. 2, the recovery of both M_1 and M_2 dropped to around 74%. The purity of M_2 decreased from 94.52% to 91.94%, while the purity of M_1 increased slightly up to 97.8% in config 2. This growth is probably due to the reception of material streams from OS2 which provides an additional input M_1 to this sorting line.

The config. 3 (Fig. 3 (c)) is based on the structure shown in Fig. 2. The recirculation factor is one of the key parameters, which refers to the percentage of the target output entering any target input. In this case, it represents the proportion of the negative output of Robot 1 going into the OS1 input. As the recirculation coefficient increases, more materials are found to accumulate in the output of Robot 1, which is likely to have a

negative impact on the recovery and purity (if other parameters remain unchanged).

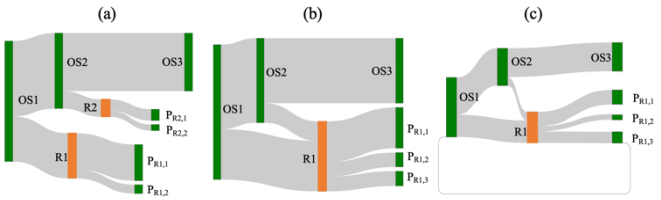

Fig. 3. Mass flow diagram of (a) config. 1, (b) config. 2 and (c) config. 3. All the simulations are optimised by automated control of the belt module.

5.2 The performance of automation control with belt module

Table 2 summaries the purity and recovery of the positive output for material M_1 ($P_{R1.1}$). When the belt module is integrated into the system, the purity and recovery of each material are improved in the corresponding positive output. Particularly, the recovery of M_1 increased by 30.5 %, growing from 47.5 % to 61.98 %. As a result, the belt module shows the desired effect in terms of improved performance.

Table 2. Summary of purity and recovery for material M_1

Scenarios	$R(M_1)_{P_{R1,1}}$	$C(M_1)_{P_{R1,1}}$
Initial output	92.25%	47.05%
Control belt speed	93.79%	61.98%
Control waste input feed	93.68%	60.65%

5.3 The benefits of belt control for different configurations: Using Monte Carlo Simulation

Monte Carlo Simulation has been adapted widely as an analysis tool to handle multiple interacting variables and uncertainty. The first step is to generate a large set of random input data following a certain distribution, and the second step is to simulate each input data by a model, and then collect and analyse all output information. In this study, the number of waste feed inputs is a variable which follows the normal distribution with a standard deviation. Finally, all the results of the evaluation factors of simulations are observed and analysed by statistical methods.

Assuming the input of each material is 2 tonnes per hour, the standard deviation is 0.2. In config. 2, the quantiles of the purity $R(M_1)_{P_{R1,1}}$, recovery $C(M_1)_{P_{R1,1}}$, belt coverage rate q, and SC are shown in Table 3, and those data of config. 2 with belt control are shown in Table 4.

It is clear from Table 3 and Table 4 that the belt coverage rate q shrunk to around 54.8% - 59.7% in the new config. 2 with belt module compared to the range of 69.8% - 83.6% in the initial config. 2, leading to the significant upward trend of the purity $C(M_1)_{P_{R1,1}}$ and recovery $R(M_1)_{P_{R1,1}}$. The difference of the $SC(M_1)_{P_{R1,1}}$ and $R(M_1)_{P_{R1,1}}$ is caused by the assumption that there is 1% of contamination (M_2) will enter the $P_{R1,1}$ output stream which should be the positive output for material M_1.

Table 3. Quantiles table of assessment factors in config. 2

Quantiles	M_1	$C(M_1)_{P_{R1,1}}$	$R(M_1)_{P_{R1,1}}$	q	$SC(M_1)_{P_{R1,1}}$
0.05	1.66	90.9%	41.6%	69.8%	42.1%
0.5	2.00	92.2%	47.1%	76.7%	47.6%
0.95	2.33	93.4%	52.5%	83.6%	53.1%

Table 4. Quantiles table of assessment factors in config. 2 with belt control

Quantiles	M_1	$C(M_1)_{P_{R1,1}}$	$R(M_1)_{P_{R1,1}}$	q	$SC(M_1)_{P_{R1,1}}$
0.05	1.67	92.5%	60.4%	54.8%	61.0%
0.5	2.00	93.8%	62.3%	57.2%	62.9%
0.95	2.33	94.8%	64.1%	59.7%	64.8%

As for the config. 3, due to the limitation of the capacity of the recirculation loop and the unpredictability of waste streams after mass balancing, unwanted overflow may occur in the Monto Carlo Simulation. Assuming belt coverage over 150% can be considered as overflow, which means the overload caused by recirculation is beyond the capacity of the system. In other words, once q > 150%, the recirculation loop is unlikely to reach mass balance within a reasonable range of q and can be referred to as a failure. This failure may be caused by a mismatch between the recirculation factor and the total waste input.

6. Conclusions

In this study a simulation model for predicting and assessing the sorting capabilities of different configurations has been developed, considering the identification and sorting limitations of robots, as well as the coordination of robots and conveyor belts in MRFs.

The MFA-based computational model has been designed and developed by modularity programme codes, which enable users to alter the variables (composition of input waste, the separation coefficient, and the configurations) to gain insight into MRF performance through factors assessment factors (purity and recovery). Several potential optimisation methods for future-proofing MRF are assessed using this modular simulation tool in the context of the evolving robotics technology within the MRF system. By simulating the two optimised configurations (two target materials for one robot and recirculation loops), this paper showcased the performance of the optimisation methods of MRF.

The shortcoming of this study is that the exploration of optimisation methods is very limited. In the future, the optimisation of the whole MRF can be explored and simulated instead of only parts. A systematic study of the effects of variables is also a potential future work.

References

[1] Kaza, S., Yao, L. C., Bhada-Tata, P., Van Woerden, F., 2018, What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. Washington, DC: World Bank.

[2] Palmer, J. R., 1999, Concept Design and Optimization of MSW Management System , Air Force Institute of Technology.

[3] Bashir, M. J. K., Chong, S.-T., Chin, Y.-T., Yusoff, M. S., Aziz, H. A., 2022, Single Waste Stream Processing and Material Recovery Facility (MRF), in *Solid Waste Engineering and Management: Volume 2*, L. K. Wang, M.-H. S. Wang, and Y.-T. Hung, Eds. Cham: Springer International Publishing, pp. 71–164.

[4] Goh, Q.-L., Chee, P.-S., Lim, E.-H., Ng, D. W.-K., 2022, An AI-Assisted and Self-Powered Smart Robotic Gripper Based on Eco-EGaIn Nanocomposite for Pick-and-Place Operation, Nanomaterials, 12/8:1317, DOI:10.3390/nano12081317.

[5] Gundupalli, S. P., Shukla, R., Gupta, R., Hait, S., Thakur, A., 2021, Optimal Sequence Planning for Robotic Sorting of Recyclables From Source-Segregated Municipal Solid Waste, Journal of Computing and Information Science in Engineering, 21/1, DOI:10.1115/1.4047485.

[6] Aschenbrenner, D., Gros, J., Fangerow, N., Werner, T., Colloseus, C., et al., 2023, Recyclebot – using robots for sustainable plastic recycling, Procedia CIRP, 116:275–280, DOI:10.1016/J.PROCIR.2023.02.047.

[7] Bobulski, J., Kubanek, M., 2021, Deep Learning for Plastic Waste Classification System, Applied Computational Intelligence and Soft Computing, 2021:1–7, DOI:10.1155/2021/6626948.

[8] Moirogiorgou, K., Raptopoulos, F., Livanos, G., Orfanoudakis, S., Papadogiorgaki, M., et al., 2022, Intelligent robotic system for urban waste recycling, in *2022 IEEE International Conference on Imaging Systems and Techniques (IST)*, pp. 1–6.

[9] Gualtieri, M., ten Pas, A., Saenko, K., Platt, R., 2016, High precision grasp pose detection in dense clutter, in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 598–605.

[10] Bircanoglu, C., Atay, M., Beser, F., Genc, O., Kizrak, M. A., 2018, RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks, in *2018 Innovations in Intelligent Systems and Applications (INISTA)*, pp. 1–7.

[11] Chu, Y., Huang, C., Xie, X., Tan, B., Kamal, S., et al., 2018, Multilayer Hybrid Deep-Learning Method for Waste Classification and Recycling, Computational Intelligence and Neuroscience, 2018:1–9, DOI:10.1155/2018/5060857.

[12] Sarc, R., Curtis, A., Kandlbauer, L., Khodier, K., Lorber, K. E., et al., 2019, Digitalisation and intelligent robotics in value chain of circular economy oriented waste management – A review, Waste Management, 95:476–492, DOI:10.1016/j.wasman.2019.06.035.

[13] Mastellone, M. L., Cremiato, R., Zaccariello, L., Lotito, R., 2017, Evaluation of performance indicators applied to a material recovery facility fed by mixed packaging waste, Waste Management, 64:3–11, DOI:10.1016/j.wasman.2017.02.030.

[14] Wilts, H., Garcia, B. R., Garlito, R. G., Gómez, L. S., Prieto, E. G., 2021, Artificial Intelligence in the Sorting of Municipal Waste as an Enabler of the Circular Economy, Resources, 10/4:28, DOI:10.3390/resources10040028.

[15] Kiyokawa, T., Takamatsu, J., Koyanaka, S., 2022, Challenges for Future Robotic Sorters of Mixed Industrial Waste: A Survey, IEEE Transactions on Automation Science and Engineering, pp. 1–18, DOI:10.1109/TASE.2022.3221969.

[16] Kleinhans, K., Hallemans, M., Huysveld, S., Thomassen, G., Ragaert, K., et al., 2021, Development and application of a predictive modelling approach for household packaging waste flows in sorting facilities, Waste Management, 120:290–302, DOI:10.1016/j.wasman.2020.11.056.

[17] Tanguay-Rioux, F., Legros, R., Spreutels, L., 2021, On the limits of empirical partition coefficients for modeling material recovery facility unit operations in municipal solid waste management, Journal of Cleaner Production, 293:126016, DOI:10.1016/j.jclepro.2021.126016.

[18] Tanguay-Rioux, F., Provost-Savard, A., Spreutels, L., Héroux, M., Legros, R., 2022, A method for assessing the performance of sorting unit operations in a material recovery facility based on waste characterizations, The Canadian Journal of Chemical Engineering, 100/9:2572–2586, DOI:10.1002/cjce.24466.

[19] Tanguay-Rioux, F., Spreutels, L., Héroux, M., Legros, R., 2022, Mixed modeling approach for mechanical sorting processes based on physical properties of municipal solid waste, Waste Management, 144:533–542, DOI:10.1016/j.wasman.2022.04.025.

[20] Rotter, V. S., Kost, T., Winkler, J., Bilitewski, B., 2004, Material flow analysis of RDF-production processes, Waste Management, 24/10:1005–1021, DOI:10.1016/j.wasman.2004.07.015.

[21] Testa, M., 2015, Modeling and Design of Material Recovery Facilities: Genetic Algorithm Approach, Doctoral disseration, Massachusetts Institute of Technology.

[22] Wolf, M. I., Colledani, M., Gershwin, S. B., Gutowski, T. G., 2013, A Network Flow Model for the Performance Evaluation and Design of Material Separation Systems For Recycling, IEEE Transactions on Automation Science and Engineering, 10/1:65–75, DOI:10.1109/TASE.2012.2203594.

[23] Połomka, J., Jędrczak, A., 2019, Efficiency of waste processing in the MBT system, Waste Management, 96:9–14, DOI:10.1016/j.wasman.2019.06.041.

[24] Velis, C. A., Longhurst, P. J., Drew, G. H., Smith, R., Pollard, S. J. T., 2010, Production and Quality Assurance of Solid Recovered Fuels Using Mechanical—Biological Treatment (MBT) of Waste: A Comprehensive Assessment, Critical Reviews in Environmental Science and Technology, 40/12:979–1105, DOI:10.1080/10643380802586980.

https://dspace.org/

Modular model and simulation for process optimisation in advanced material recovery facilities (MRFs)

Liu, Milan; Grimes, Sue; Salonitis, Konstantinos; Litos, Lampros

2024
Elsevier
https://doi.org/10.1016/j.procir.2024.07.050
Liu M, Grimes S, Salonitis K, Litos L. (2024) Modular model and simulation for process optimisation in advanced material recovery facilities (MRFs). Procedia CIRP, Volume 128, 2024, pp. 250-255

Downloaded from a DSpace repository. https://dspace.org/