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# Optimal location and operation of waste-to-energy plants when future waste composition is uncertain

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## Abstract

In many countries, waste management is increasingly geared towards a circular economy, aiming for a sustainable society with less waste generation, fewer landfills, and a higher rate of recycling. Waste-to-Energy (WtE) plants, which convert waste into heat and energy, can contribute to the circular economy by utilizing types of waste that cannot be recycled. Due to the varying quality of sorting and socioeconomic conditions in individual regions, the waste composition differs between regions and has an uncertain future development. Waste composition significantly affects the operation of WtE plants due to differences in energy potential. This paper supports strategic capacity planning for waste energy recovery by introducing a two-stage stochastic mixed-integer linear programming model that captures waste composition uncertainty through scenarios of possible future development. The results of the model provide insights into the economics of operation and identify important factors in the sustainability of the waste handling system. The model is demonstrated on an instance with six scenarios for waste management in the Czech Republic for the year 2030. The solution of the proposed model is to build 14 new WtE plants with a total capacity of 1970 kt in addition to the four existing plants with a capacity of 831 kt. The annual energy recovery capacity is expected to increase almost four times to satisfy EU directives that restrict waste landfilling.

**Keywords:** Stochastic programming, facility location, multi-commodity, mixing approach, lower heating value, MILP

## 1 Introduction

Energy consumption is increasing worldwide (IEO 2020), and the energy demand is primarily met by fossil fuels, whose supply is limited (Agbulut and Saridemir 2019). Given the current trend of increasing energy consumption, it is necessary to search for alternative sources of power (Agbulut et al. 2019) while searching for the best opportunities to reach targets for reductions in emissions (Marinakakis et al. 2017). At the same time, there are many types of waste that cannot be recovered materially but contain a significant energy potential. Combining the growing demand for energy, the search for alternative sources, and the need to process waste, the use of waste to produce energy seems to be an ideal solution to several simultaneous problems. An integral part of efficient waste management

(WM) is energy recovery for otherwise unusable waste (**Ng et al. 2014**), and Waste-to-Energy (WtE) plays an important role in the circular economy.

The largest category of municipal solid waste (MSW) is mixed municipal waste (MMW), which, despite optimistic scenarios for sorting various commodities, still represents a significant part of the total amount of MSW. The geographical location and the economic development of countries significantly affect the generated MSW (The World Bank 2012). Components such as bio-waste, plastics, paper, glass, and metals have the largest presence in MSW. Each type of waste has different thermochemical properties, which are often examined in connection with energy recovery (**Zhou et al. 2015**). The energy amount which can be recovered from waste is expressed by the calorific value, which is a measurement of the energy or heat released (kJ or kcal) when 1 kg of material is completely combusted in the presence of air or oxygen (**Battle et al. 2014**). In the case of MMW, the calorific value can be comparable to some fossil fuels, such as brown coal, which has wide industrial use as a source of thermal energy. At the same time, there may be large differences in the properties of waste between individual micro-regions due to both the efficiency of separation and the socioeconomic conditions.

In relation to energy production, it is necessary to analyze the composition of waste and evaluate its energy potential. In addition to MMW, other types of waste, such as bulky waste (**Šomplák et al. 2019**) and residual waste flows from recycling lines (**Brouwer et al. 2018**), are also suitable for energy recovery. For this reason, it is necessary to deal with the calorific value of individual types of waste. With the transition to a circular economy and new EU regulations, the waste composition may change significantly in the coming years. This is partly due to increasing levels of waste separation, with waste being broken down into new types of waste with different properties. The potential changes in waste composition represent a source of uncertainty in the operation of WtE plants and influence the entire waste supply chain.

Due to the uncertainty in the future composition of waste, it is imperative to consider strategic planning in the field of treatment infrastructure. Decisions are made based on provided plans and predictions from techno-economic models. However, not all decision-making considers the composition of waste and responds appropriately when dimensioning individual projects or designing a complete network. The return on energy sales is one of the important financial revenues for WtE plants (**Agaton et al. 2020**). The composition of the waste affects the energy balance of the WtE plant and has a major impact on the amount of incinerated waste. The investment into a WtE plant and its subsequent operation also depends on waste processing revenues (i.e., gate fee). If the waste turns out to have a higher or lower calorific value than what was expected when constructing a plant, it may not be possible to incinerate the planned amount of waste, which in turn has direct economic consequences for the system. Any excess waste must be redirected, which can be difficult due to regulatory compliance and can lead to a high additional cost.

This paper proposes a new mathematical model, which is a two-stage stochastic mixed-integer linear programming (TS-MILP) model, to support the strategic planning of WtE plants from the perspective of a government that seeks to minimize losses from handling waste. This involves determining locations and treatment capacities for individual plants while taking into account the uncertainty regarding the future composition and energy contents of waste. The issue of waste heterogeneity in relation to energy potential can be described by means of a mixing problem. That is, a single WtE plant receives flows of waste from different sources so as to obtain a mix of waste that can effectively be processed to generate heat and electricity. The principles of the mixing problem can be implemented into tools for the support of strategic WM planning using mathematical programming. These tools based on mathematical programming provide a greater insight into the addressed issues and support

managerial management. However, the final decision cannot be made without quality leadership, which must evaluate the obtained results in the context of the set goals.

The remainder of the paper is organized as follows. **Section 2** gives a literature review on the current state of optimization tools used in WM. Then, **Sect. 3** provides the problem description, describing the main idea of the mixing approach and outlining the important attributes of waste when used for energy recovery, and the mathematical model. **Section 4** is devoted to the application of the model to data from the Czech Republic. The most important results and outcomes are highlighted in **Sect. 5**, together with suggestions for future research.

## 2 Literature review

Research on a circular economy deals with how to improve the quality of the environment and human life through a more efficient industry. **Varbanov et al. (2021)** discussed the benefits of recycling, reuse, energy-saving, and waste prevention, while **Fan et al. (2020)** sought to propose improvements to current WM systems, focusing on recycling and WtE. **Samson (2020)** mentioned that the supply chain should be prepared for a big shock, be it a pandemic or natural catastrophe.

Various challenging optimization models have been developed to support strategic planning in waste management (**Van Engeland et al. 2020**). Some past studies have dealt with the optimization of waste flows within a network and seeking the best location for WtE plants (**Hu et al. 2017**). Conceptual planning approaches usually deal with determining the location of facilities (**Boccia et al. 2018**) and their capacities (**Boonmee et al. 2018**), as well as the selection of collection routes (**Far-rokhi-Asl et al. 2020**), including transshipment stations (**Yadav et al. 2018**) for efficient transportation and ensuring the sustainability of the whole processing chain. **Asefi and Lim (2017)** dealt with a complex model describing a WM system considering multiple economic, environmental, and social objectives. An interesting study by **Mitropoulos et al. (2009)** studied location-planning of facilities for solid waste treatment. The authors introduced exact and heuristic approaches, after creating a mathematical model based on mixed-integer programming. The developed model was applied to a case study in Greece, where the model took into account the tradeoff between effective high-cost technology and cheaper options with no treatment process.

A comprehensive review of sustainable supply chain models (**Barbosa-Póvoa et al. 2018**) defined potential future directions in strategic planning, and one of them is the consideration of waste heterogeneity and its influence on the WtE plant operation. The review analyzed over 200 articles presented after the year 2000, with a larger proportion of newer ones. The articles were grouped according to different decision levels in the supply chain, the monitored criterion, and the selected solution procedure. Another review was presented by **Kazemi et al. (2017)**, who focused on reverse logistics and closed supply chain management. The analysis of hundreds of papers showed that the research gaps and opportunities primarily lie in utilizing real collected data and studies based on real industrial cases.

Real case studies show that it is necessary to track individual waste flows from a quantitative and a qualitative point of view. Specifically, an essential element for the financial sustainability of a WtE plant is the energy demand, and the efficiency of its fulfillment depends on the parameters of the incinerated waste (**Sipilä, 2016**). Since the operation of a WtE plant is influenced by waste heterogeneity, it must be taken into account when designing the plant or whole waste management system (Shi et al. 2016). The methods developed until now usually have not considered how the composition of waste differs from location to location. Many types of waste are suitable for energy

utilization, e.g., some fractions of bulky waste (**Šomplák et al. 2019**) or combustible industrial waste (**Garcés et al. 2016**). The variability of waste composition (**Czajczyńska et al. 2017**) and its calorific value (**Zhou et al. 2015**) is a significant problem in strategic planning and prediction of future scenarios. However, for an efficient supply chain, this is key data. The articles mentioned above either do not consider this fact, or they use an average waste composition without considering individual types of waste. To ensure the long-term sustainability of the WM, it is necessary to be adequately prepared for several different potential development scenarios.

Some studies have addressed the design of one specific facility while considering the operating conditions and calorific value of the waste. However, in the case of broader conceptual planning over a large territory, this aspect is usually not considered in full. **Mohammadi et al. (2019)** described a robust model of WM, including the calorific value of waste. However, the calorific value was only considered for residual flows, which were considered as a homogeneous whole with fixed thermochemical properties. Neglecting the heterogeneity of waste, its calorific value and the WtE plant's operating conditions can affect the cost for waste processing and facility sustainability (**Touš et al. 2014**).

A key aspect of effective planning is an accurate forecast of future developments. All future estimates include uncertainty, which must be addressed to obtain robust results (**Tirkolaei et al. 2020**). The uncertainty can be handled using stochastic programming techniques. **Jammeli et al. (2019)** introduced a bi-objective stochastic model for household waste collection, where uncertainty was considered with respect to population size. The model was tested in a case study, and the obtained results showed economic savings and a reduced environmental impact. **Hu et al. (2017)** presented a multi-criteria stochastic model that dealt with the optimal location and capacity of WtE plants. The uncertainty was discussed from the point of view of MSW generation as a whole, not as a flow of several waste types with different properties. **Gambella et al. (2019)** presented a multi-period model with realistic constraints for waste treatment facilities. Another two-stage stochastic model was introduced by **Zhen et al. (2019)**, who dealt with a closed-loop supply chain and its operational costs under uncertain demands and returns. Scenario-based models are not exceptional nowadays: for example, a two-stage model was applied to an internal waste resource system by **An et al. (2016)**. **Kůdela et al. (2019)** mainly focused on multi-stage models describing WtE plants and mechanical biological treatment in relation to the recycling targets of the EU and addressed the uncertainty of future waste generation. A greater emphasis was placed on WtE plants and transportation in the work of **Hrabec et al. (2020)**, where the authors described in more detail the design of the considered scenarios with respect to possible deviations in the prediction. Other recent studies within WM dealt with the Coronavirus pandemic. A paper by **Tirkolaei et al. (2021)** presented a location-routing problem for medical waste, where a fuzzy chance-constrained technique was used to address uncertainty in demands.

In a detailed review, **Hannah et al. (2020)** investigated different objectives and constraints in solid WM. They presented an analysis of over 150 articles, some of which were devoted to stochastic optimization and some of which considered uncertainty from the point of view of waste generation. However, these articles did not aim at strategic planning of WtE plants in connection with the uncertainty in the calorific value of the incinerated material. An interesting perspective was provided by **Atabaki et al. (2020)**, who presented a stochastic model describing a complex processing chain. Uncertainty was addressed from several points of view, such as production, operating costs, and demand for materials. A study by **Xu et al., (2018)** presented a genetic algorithm to support MSW management with fuzzy constraints related to facility capacity. Another model capturing uncertainty in WM was provided by **Wu et al. (2018)**, where optimization with interval numbers was used to minimize emissions.

Furthermore, a pair of consecutive articles by **Cheng et al. (2017a, 2017b)** presented a comprehensive study of WM in Beijing based on scenarios of possible developments using fuzzy hierarchical programming. The scenarios represented the possible developments of solid waste treatment policies and differed in representing individual types of waste treatment facilities. However, from the point of view of a WtE plant in the context of extensive conceptual planning, the current studies do not take into account the key variability in the calorific value of waste, its various types, and its direct impact on operation, including economic sustainability. Given that investment in these facilities and the consequent operating costs represent a significant part of the total WM expenditure, these aspects need to be taken into account.

The described shortcomings are addressed in this paper. Similar research gaps regarding the waste composition aspect were identified by **Tirkolaee et al. (2020)**, where the design of an urban WM was investigated. The MSW composition is modelled via scenarios to obtain robust results. The effort of the presented paper is to further extend the implications resulting from waste composition issues and evaluate their impact on WtE plants. The newly developed approach can track flows of waste with additional properties. Individual scenarios can be included in strategic planning through a stochastic programming model which describes uncertainty in the waste generation and composition while considering the operational conditions of the WtE plants. The approach is based on real industrial cases where waste heterogeneity causes operational difficulties. The goal is to provide new insights into this WM issue while presenting a model that can be a part of managerial tools to support decision-making.

### **3 Mathematical model**

#### *3.1 Problem description*

Waste represents a significant energy potential. Therefore, combustible waste should be used for energy recovery instead of landfilling (**Giugliano et al. 2008**). A WtE plant uses waste for both heat supply and electricity generation. Heat and electricity sales depend on prices and demands and represent almost 50% of a WtE plant's income (**Ferdan et al. 2015**). The heat supply is limited by its demand in the WtE plant region, but any excess power can be converted into electricity. The overall effectiveness of the cogeneration of heat and electricity is higher than a separated production, and 30-40% more energy can be produced (**Sipilä 2016**).

WtE operations are limited by the maximum power restriction of the designed plant, meaning that the planned amount of waste cannot be processed if the calorific value of waste is higher than anticipated. This results in a lower income from waste treatment and has a significant impact on the economic sustainability of the WtE plant. Conversely, suppose the incinerated mixture is too humid due to the presence of bio-waste or the absence of heating components. In that case, the incinerator is forced to supply the missing heat in the grate incinerator with natural gas. Since the calorific value of the mixture cannot go outside of the permitted range, the calorific value of the incinerated mixture plays an important role in ensuring the proper operation of a plant. The main challenge lies in the uncertainty of the calorific value, which is highly dependent on the waste composition and content of water. The operation of a WtE plant is also restricted by the maximum and minimum amount of waste that can be incinerated.

The calorific value of a material can be expressed using the lower heating value (LHV), which represents the total energy content without vaporization (**Bilgen et al. 2012**). To produce electricity, heated water is converted into steam, which drives a generator. The steam, which is still very hot, then goes to a heat exchanger, where it transfers heat to the heat supply system and then condenses. Due to

changing the water phase during cogeneration, it is necessary to use the calorific value in the form of LHV, as it considers the latent heat for the conversion of the state of water. In the rest of this work, the calorific value of the incinerated material is measured using LHV.

Separation and recycling are important elements in the management of MSW, especially in the transition to the circular economy (Genovese et al. 2017). However, not all separated waste can be recycled and reused as secondary raw material. The recycling efficiency for some problematic MSW fractions is only around 50% (Eygen et al. 2018), leading to the formation of many types of waste suitable for energy recovery, ideally with an LHV greater than 6 MJ/kg. The main types of waste used for energy production include MMW and bulky waste, whose composition is very heterogeneous. **Table 1** gives an overview of the most common types of waste and their LHV. The proportion for each waste type of MSW is given based on the average amount of waste generated over the period 2016-2018 in the Czech Republic (ISOH 2018). The waste characteristics vary from region to region depending on socio-economic conditions, leading to the wide ranges listed. Therefore, the resulting mixture entering the WtE plant has an a priori unknown and unpredictable LHV.

When planning for a future waste handling system based on WtE plants, the main decisions are where to locate new WtE plants and how large their respective capacities should be. These decisions must take into account how the future waste generated in different regions may vary in quantity and type, and thus also in terms of the calorific value of the waste. The aim is to provide an optimal supply chain for waste management from an economic point of view, taking into account the operating conditions of the WtE plants. Once decisions have been made on the locations and capacities of WtE plants, transportation of waste from different regions and into WtE plants must be handled. To reduce operational problems and maximize the economic viability of WtE plants, a careful mix of incoming types of waste may be needed, which we refer to as a mixing approach. Therefore, it is necessary to properly control the composition of waste flows in the transportation network.

**Table 1** Overview of types of waste and their LHV

Waste type	Proportion of MSW	LHV Range [MJ/kg]	Source
Plastic	2.7%	17.1–38.6	Hla and Roberts (2015)
Paper	9.3%	10.2–15.1	Hla and Roberts (2015)
Glass	2.5%	0.0	Not combustible
Bio-waste	14.2%	3.8–5.5	Hla and Roberts (2015)
Textile	0.5%	15.2–19.6	Hla and Roberts (2015)
Wood	1.3%	15.7–18.2	Hla and Roberts (2015)
Metal	5.0%	0.0	Not combustible
MMW	48.8%	7.0–11.0	Doležalová et al. (2013)
Bulky	9.9%	18.0–22.0	Garcés et al. (2016)

The mixing approach involves more detailed modeling of conditions at specific locations and operations at WtE plants. The key elements of the approach are shown in **Fig. 1**. Residual waste that cannot be processed at WtE plants must be sent to other types of facilities, such as landfills or cement plants, where waste can be disposed of without concerns regarding its calorific value. Overall, it is necessary to consider transportation costs, treatment costs, and investment costs for new plants.

### 3.2 Model overview

The following TS-MILP model is proposed as a tool to support decision-making in the design of WtE networks. The first stage decisions are to fix the locations of the WtE plants and their capacities. At this point in time the future amounts of waste from different regions and their associated LHV are unknown. The second stage of the model begins when the amount of waste and the corresponding LHV becomes known. Then, decisions must be made regarding transportation within the network and treatment in WtE plants as well as other facilities whose operation is independent of the LHV of the waste. In the proposed model, the uncertainty with respect to waste amounts and LHVs is discretized, meaning that potential outcomes are represented using discrete scenarios. In other words, a deterministic equivalent program is presented, and uncertainty is implemented using a set of scenarios, which represents possible developments of waste generation and waste composition.

The main output of the TS-MILP is the decisions of where to build individual WtE plants and which capacity each plant should have to ensure an economically sustainable solution if any of the considered scenarios are realized. This is the here-and-now approach, where the goal is to find a compromise between all scenarios with an emphasis on the more probable ones. The key elements of the modeled tasks are shown in Fig. 2.

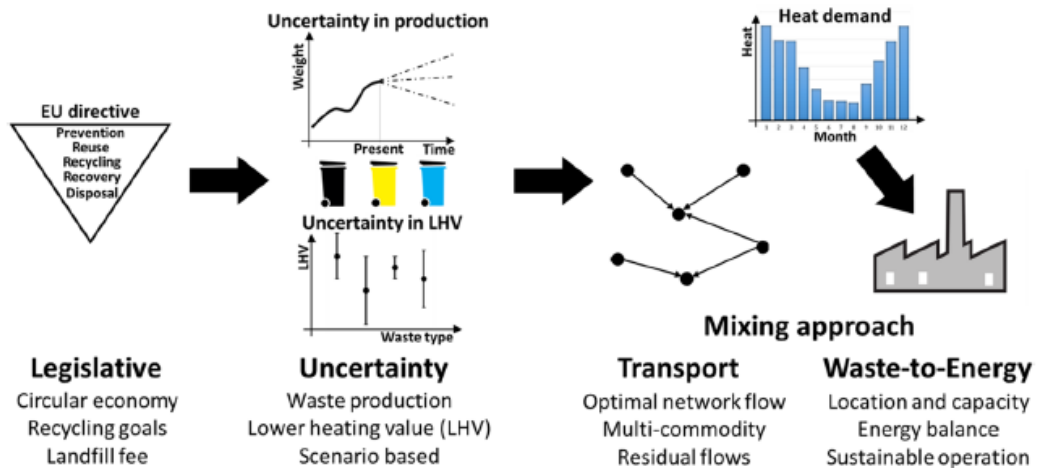


Fig. 1 Scheme describing the links between the causes, the consequences, and the mixing approach to the introduced problem

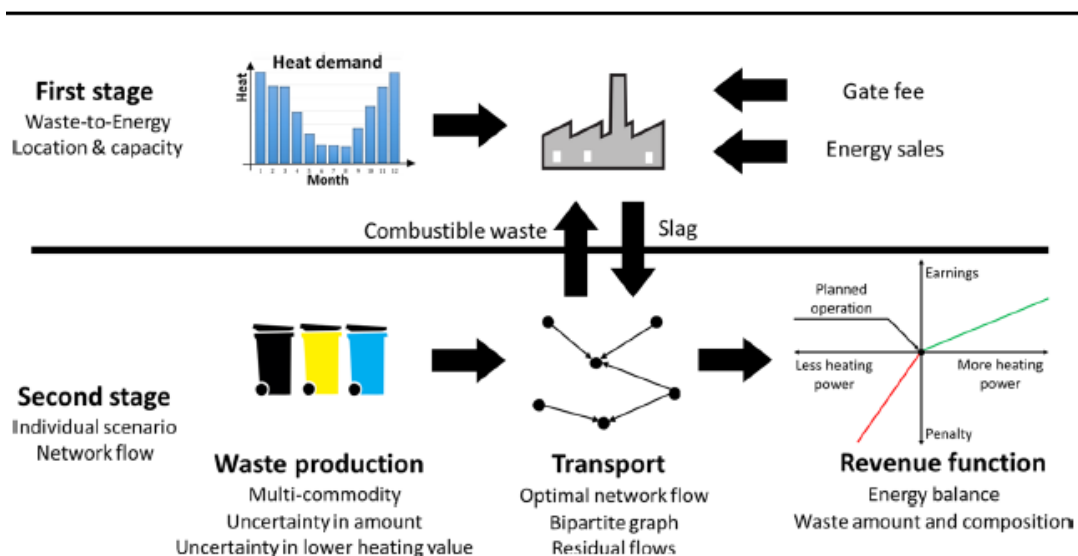


Fig. 2 Scheme of a two-stage model and an overview of the included elements

The model is based on the flow in a network which is described by an oriented bipartite graph. This corresponds to the one-way transportation infrastructure where a waste flow is from a source of waste to a possible treatment node. This graph can be used to describe waste transportation in more detail. Transportation costs depend non-linearly on distance (**Gregor et al. 2017**), and thanks to the bipartite graph, each arc can be assigned a corresponding unit price for the amount of waste, as the arcs are clearly determined by the start and endpoint.

The model considers different types of waste, which can be treated in given types of plants and can design a suitable supply chain ready to effectively manage and adapt to changes in the system without major interventions. The model includes the treatment and transportation cost, also considering residual flows. The demand for heat defines the possible levels of energy utilization at each location, resulting in a non-linear relationship between the processing costs and the plant's capacity that affects the maximum heat supply (**Ferdan et al. 2015**). All non-linear dependencies are modeled using special ordered set (SOS) variables (**Williams 2009**).

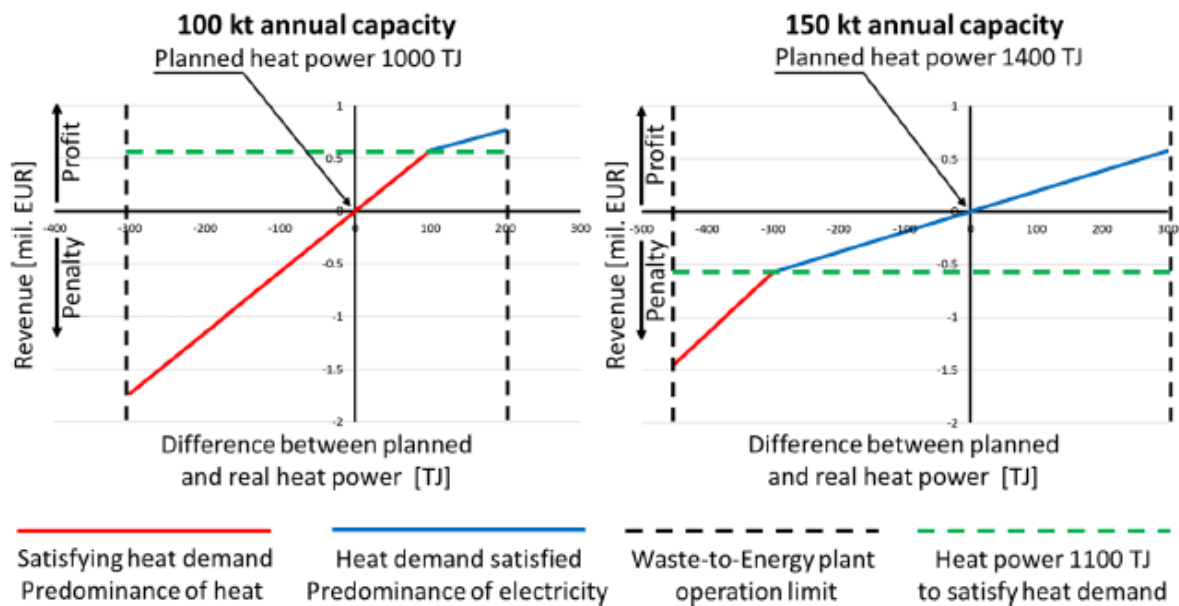
### *3.3 Revenue function*

The model ensures feasible conditions for the operation of WtE plants. To represent the economic result, a revenue function is designed which considers the amount of waste received and the LHV of the waste mixture, and which is thus able to reflect the heat power. Negative deviations from the optimal heat power change the net produced heat and electricity, which results in lowered profits from energy sales, while positive deviations lead to higher earnings than expected. At the same time, it is necessary to include limits in the form of the maximum and minimum heat power, which is determined by the parameters of the individual WtE plants.

The design of the revenue function is based on the principle of simultaneous production of heat and electricity. Electricity within the distribution network can be supplied across the entire territory, whereas heat can only be distributed in the vicinity of the plant. Its sales depend on the heat demand, which varies throughout the year. The peaks are during the winter months, and the reduction might be around 80% during the summer. The main idea is that the WtE plant remains in this production mode until the heat demand is met. Subsequently, all remaining power serves only for electricity production. Therefore, if the operation of a WtE plant deviates from the planned (i.e., optimal) point, the revenue depends on whether or not this change is reflected in heat sales. We assume that the corresponding energy sales relative to the capacity are already included in the processing costs. Thus, the revenue function represents economic effects of deviations from the planned operation. Revenue functions are defined for each potential WtE plant and corresponding plant capacity, considering energy prices and production efficiencies (**Touš et al. 2015**). Revenue functions for a given plant and two different capacity alternatives are shown in **Fig. 3**.

The revenue function to the left in Fig. 3 shows a case where the heat demand for the plant location is higher than a WtE plant with a capacity of 100 kt can produce under the planned conditions (with coordinates corresponding to the origin). However, the heat demand can be fulfilled by the incineration of a waste mixture with a higher LHV while obtaining additional earnings from energy sales. When heat demand is satisfied, any excess energy is predominantly transformed into electricity, which is less effective. In a case of less heat power, a WtE plant produces less heat and electricity, which results in lower profits. The revenue function to the right shows the corresponding plant with a capacity of 150 kt, in which case the cusp reflecting heat demand is to the left of the origin. This means that more heat power mainly generates electricity, while less heat power influences only electricity sales. Due to the consideration of the overall annual planning, the model does not allow incinerating

more waste than the specified maximum capacity. While it is possible to deviate from the expected quantity within shorter periods, it is not possible to exceed the maximum permitted capacity in the long term. The revenue function is piece-wise linear, and it is implemented using SOS variables.



**Fig. 3** Demonstration of penalties functions formulation. Heat power is expressed as the product of the amount of waste and its LHV

### 3.4 Optimization model

The following sets are used in the TS-MILP model.

Sets	
$E$	set of arcs between sources of waste and treatment facilities
$F$	set of potential locations for WtE plants
$I$	set of all nodes
$I^E \subset I$	subset of nodes including only WtE plants with corresponding capacities
$I_j^F \subset I$	subset of nodes including only WtE plants with capacities in location $f$
$I^P \subset I$	subset of nodes including only sources of waste
$I^T \subset I$	subset of nodes including only other types of treatment facilities
$K$	set of breakpoints for the piece-wise linear revenue function
$S$	set of scenarios

The sets of nodes are illustrated in **Fig. 4**. The underlying graph has three main subsets of nodes. One subset represents the sources of waste, with different types of waste being generated in different regions. These nodes are linked to treatment facilities, including the potential new WtE plants. The potential WtE plants are modeled using several nodes, each node corresponding to a combination of a plant location and a plant capacity. The third subset of nodes is other types of existing facilities, such as landfills and cement plants, where residual waste can be redirected. The network has arcs only from source nodes to treatment nodes.

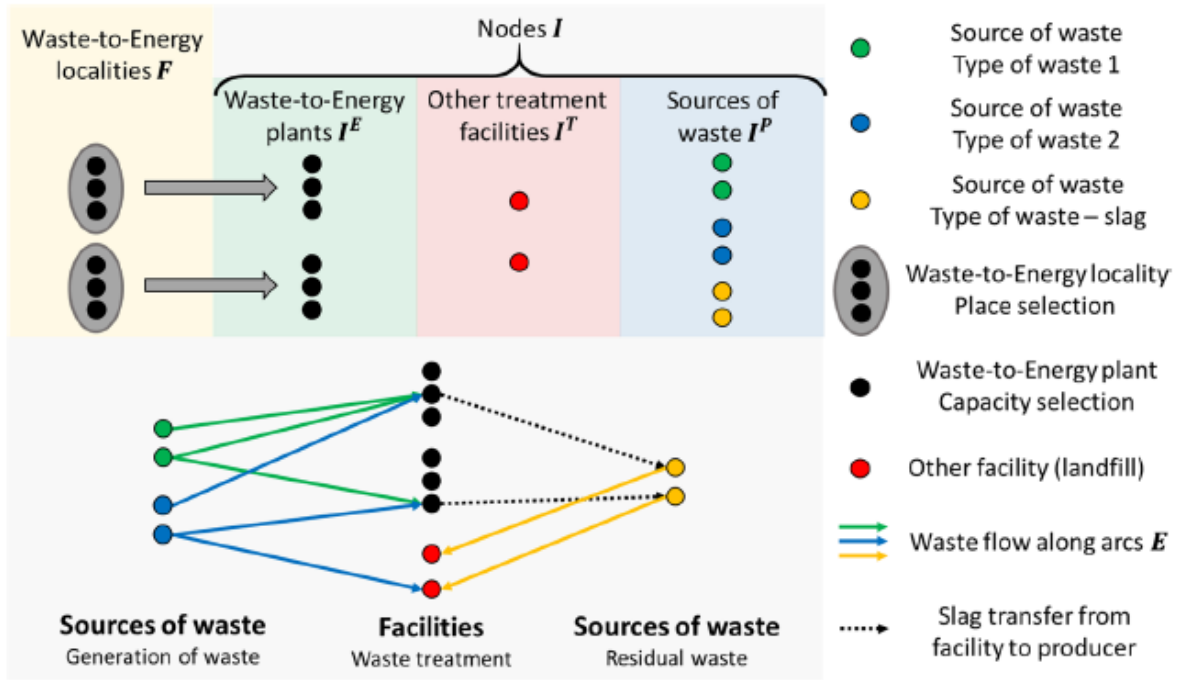


Fig 4 Illustration of graph connections showing individual sets of nodes in the model.

There is one exception to this, related to residual flows from WtE plants in the form of slag. To keep the bipartite structure of graph, the slag is allowed to be transferred without using flow in the network from a node representing a WtE plant to a waste source node in the same location.

The following parameters and variables are used in the model.

Parameters	
$B_{i,j}$	equal to 1 if there is a possible transfer of slag from the WtE plant in node $j$ to a waste source node $i$ from where the slag is transported to a landfill, and 0 otherwise, [-]
$C_{i,k}^{REV}$	revenue at plant $i$ when heat power deviation is at breakpoint $k$ , [EUR]
$C_i^{TREAT}$	treatment cost in the facility located at node $i$ , [EUR/kt]
$C_e^{TRANS}$	transportation cost along arc $e$ , [EUR/kt]
$C_i^{WtE}$	treatment cost at WtE plant at node $i$ , [EUR]
$G_i$	treatment capacity of node $i$ , [kt]
$H_{e,s}$	LHV of transported waste along arc $e$ in scenario $s$ , [-]
$L_i^{MAX}$	maximum LHV of incinerated waste in WtE plant $i$ , [TJ/kt]
$L_i^{MIN}$	minimum LHV of incinerated waste in WtE plant $i$ , [TJ/kt]
$M_{e,i}$	equal to 1 if arc $e$ enters node $i$ , equal to -1 if arc $e$ leaves node $i$ , and 0 otherwise, [-]
$O_{i,s}$	amount of waste at node $i \in I^P$ in scenario $s$ , [kt]
$P_s$	probability of scenario $s$ , [-]
$Q_i^{MAX}$	maximum heat power of WtE plant at node $i$ , [TJ]
$Q_i^{MIN}$	minimum heat power of WtE plant at node $i$ , [TJ]
$Q_i^{REF}$	preferred heat power of WtE plant at node $i$ , [TJ]
$R_e$	coefficient of waste mass reduction by waste treatment assigned to arc $e$ , [-]
$U_{i,k}$	heat power deviation of WtE plant at node $i$ and breakpoint $k$ , [TJ]
Variables	
$x_{e,s}$	the amount of waste transported along arc $e$ in scenario $s$ , [kt]
$y_i$	binary decision variable, equal to 1 if WtE plant at node $i$ is built, and 0 otherwise [-]
Special ordered sets, type 2	
$w_{i,k,s}$	variable for the revenue function of the WtE plant at node $i$ , when the heat power deviation is equal to breakpoint $k$ in scenario $s$ , [-]

### 3.5 Objective function

The objective function (1) consists of the total cost of waste processing. The first part of the objective function (1) relates to the first stage and captures the total investments and operational costs of the WtE plants. At each location, several alternatives are given for the capacity of a plant, differing in the waste processing unit cost and the revenue function. The investments must be distributed across the entire lifespan, and the cost is therefore adjusted to represent the corresponding planning horizon. The second stage-related part of the objective function captures the effect of each scenario, i.e., the sum of waste treatment costs in other facilities, transportation costs, and contributions from a revenue function that reflects the changes in the LHV of incinerated waste in WtE plants and adjusts the resulting operational costs.

$$\min \sum_{i \in I^E} C_i^{WtE} y_i + \sum_{s \in S} P_s \left( \sum_{e \in E} \sum_{i \in I^T} C_i^{TREAT} M_{e,i} x_{e,s} + \sum_{e \in E} C_e^{TRANS} x_{e,s} - \sum_{i \in I^E} \sum_{k \in K} C_{i,k}^{REV} w_{i,k,s} \right) \quad (1)$$

### 3.6 Constraints

Constraints (2) ensure that at most one WtE plant at each location is open, with a corresponding capacity reflecting given configurations of the techno-economic model (Ferdan et al. 2015).

$$\sum_{i \in I_j^E} y_i \leq 1, f \in F. \quad (2)$$

The next constraints enforce capacity restrictions. Constraints (3) are related to the WtE plants. The middle part of constraints expresses the amount of waste transported to a given facility, while the right-hand side and left-hand side represent the minimum and maximum capacity of the corresponding WtE plants. Constraints (4) enforce capacity restrictions for each node representing other types of treatment facilities. Sources of waste are considered by constraints (5). The left-hand side expresses waste generation in the node,  $O_{i,s}$ , transfer of residual waste from WtE plants back to the source nodes, and the flow of waste from the source to treatment facilities. The right-hand side is equal to zero to ensure that the flow is balanced.

$$0.5y_i G_i \leq \sum_{e \in E} M_{e,i} x_{e,s} \leq y_i G_i, i \in I^E, s \in S \quad (3)$$

$$\sum_{e \in E} M_{e,i} x_{e,s} \leq G_i, i \in I^T, s \in S. \quad (4)$$

$$O_{i,s} + \sum_{e \in E} \sum_{j \in I^E} R_e B_{i,j} M_{e,j} x_{e,s} + \sum_{e \in E} M_{e,i} x_{e,s} \leq 0, i \in I^P, s \in S. \quad (5)$$

Constraints (6) are connected to the revenue function. This piece-wise linear function is implemented by using the SOS2 variables  $w_{i,k,s}$ . It is a function of the difference between the planned heat power and the actual heat power that comes from the amount of incinerated waste and its properties. The right-hand side of the equation expresses this difference, which is then set equal to the left-hand side that involves the SOS2 variable. The SOS2 variables can then be used in the objective function (1).

$$\sum_{k \in K} U_{i,k} w_{i,k,s} = \sum_{e \in E} H_{e,s} M_{e,i} x_{e,s} - Q_i^{REF} G_i y_i, \quad i \in I^E, s \in S. \quad (6)$$

According to the technical parameters of the grate incinerator, we have to ensure a certain quality of the waste mixture used. The total heat power based on the amount of waste and its LHV must not exceed the maximum nor fall behind the minimum grate incinerator performance, respectively. This condition is modeled by using two sets of constraints. First, constraints (7) enforce the maximum grate incinerator performance, where the left side reflects the total energy in the incinerated waste, while the right side reflects the grate incinerator parameters. Constraints (8) handle the minimum grate incinerator performance.

$$\sum_{e \in E} H_{e,s} M_{e,i} x_{e,s} \leq Q_i^{MAX} G_i y_i, \quad i \in I^E, s \in S. \quad (7)$$

$$\sum_{e \in E} H_{e,s} M_{e,i} x_{e,s} \geq Q_i^{MIN} G_i y_i, \quad i \in I^E, s \in S. \quad (8)$$

Another operating condition relates to the LHV of incinerated waste. A WtE plant cannot incinerate waste outside the minimum and maximum operating limits. Constraints (9) describe that the incinerated mixture must have equal or lower LHV than a single type of waste with an LHV equal to  $L_i^{MAX}$ . On the other hand, constraints (10) require that the mixture must have a higher LHV compared to waste that has an LHV of  $L_i^{MIN}$ .

$$\sum_{e \in E} H_{e,s} M_{e,i} x_{e,s} \leq \sum_{e \in E} L_i^{MAX} M_{e,i} x_{e,s}, \quad i \in I^E, s \in S. \quad (9)$$

$$\sum_{e \in E} H_{e,s} M_{e,i} x_{e,s} \geq \sum_{e \in E} L_i^{MIN} M_{e,i} x_{e,s}, \quad i \in I^E, s \in S. \quad (10)$$

Constraints (11) and (12) form part of the definition for the SOS2 variables  $w_{i,k,s}$  used to correctly calculate the value of the revenue function. Finally, constraints (13) and (14) define the domains of the flow variables  $X_{e,s}$  and the binary variables  $y_i$ .

$$\sum_{k \in K} w_{i,k,s} = 1, \quad i \in I^E, s \in S. \quad (11)$$

$$w_{i,k,s} \geq 0, \quad i \in I^E, k \in K, s \in S. \quad (12)$$

$$x_{e,s} \geq 0, \quad e \in E, s \in S. \quad (13)$$

$$y_i \in \{0;1\}, \quad i \in I^E. \quad (14)$$

## 4 Computational study

### 4.1 Description of basic characteristics

The benefit of the proposed approach is verified in a case study for the Czech Republic. The study is focused on the planning of capacities of WtE plants and their distribution with respect to residual MSW flows suitable for energy recovery. The focus is the state of the WM in the year 2030, which can provide appropriate insight into the planning of new WtE plants. The calculation is performed on the actual structure of micro-regions in the Czech Republic. Due to the uncertain development of living conditions, governmental measures, and the overall development of WM, several different scenarios are taken into account where the LHV and amount of waste from different regions vary.

MMW, bulky waste, and residual waste from plastics and paper recycling are included in the case study. The basic scenario of waste generation is estimated according to a point forecast of the development of WM that is performed based on trend analysis (Pavlas et al. 2020) from historical data (ISOH 2018) in individual regions. In the same way, the LHV of MMW is estimated for each region according to its composition. Residual waste from recycling is determined by a recycling efficiency dependent on the separation rate (Pluskal et al. 2021). Unique data regarding the generation and LHV of waste are assigned to each region. Due to regulatory authorities, bulky waste must be used for energy recovery because it has a high energy potential, and this type of waste can therefore not be sent to a landfill in the case study.

The flow network contains 206 nodes that represent individual micro-regions. Suitable locations and capacities for WtE plants are selected according to heat demands to achieve high cogeneration efficiency and subsequent energy sales. There are 32 micro-regions with the possibility of building a new WtE plant. In addition, four already existing plants are also included in the calculations. At each potential location, up to five different capacities are considered by taking into account conditions given by the legislation for operations of large WtE plants in the given regions. Other considered treatment facilities include landfills and cement plants. In the case of landfills, the current free capacity is not addressed, while cement plants are limited by operating capacity and use only high-calorific waste, i.e., residues from recycling. There are five existing cement plants in the Czech Republic and 110 landfills. Cement plants are not price differentiated, and neither are landfills. However, individual types of facilities reflect a hierarchy of treatment preferences, which is implemented as part of the processing costs. Cement plants use waste as fuel, so from an economic point of view, it is an advantageous solution, and, in the model, this type of processing is free. The least preferred treatment is landfilling, where a processing cost for landfilling waste is considered according to the valid legislation of the Czech Republic. After incineration, residual waste is considered a form of slag, whose amount is estimated to be 25% of the original amount of waste, regardless of its composition. Slag is landfilled without any processing costs, as this type of residual waste is considered a building material, and landfills use it for surface adjustment.

Two directions of possible deviations from the base scenario can be identified. One of them reflects a faster fulfillment of recycling targets. In this case, a significant decrease of MMW and an increase in residues from recycling will be observed. As a second direction, the current situation resulting from

the COVID-19 pandemic is associated with an increase in MMW and a decrease in sorted waste. This leads to an opposite change of material flow compared to the previous case. Corresponding scenarios are constructed through a redirection of individual material flows from MMW to separate types of waste and from separate waste to MMW, respectively. The change from the base scenario S1 is set to 30%. These scenarios are then duplicated with an additional restriction for cement plants. It is necessary to involve the case where cement plants cannot accept all available residues from sorting due to interruptions of operations or by receiving other types of additional waste that reduces the free capacity for municipal waste. The restriction is implemented by setting the maximum treated waste in cement plants equal to 50% of the total sorting residues in the base scenario, S1. Another condition in the base scenario, S1, is related to landfills and is set by restricting the maximum landfilled waste to 10% of the overall MSW generation.

In total, six scenarios are included in the case study. The generation of the included types of waste in the individual scenarios is given in **Table 2**, together with the considered probability of the scenarios. Base scenario S1 and scenario S4 are considered most likely because they correspond to a prediction estimated using the historical development of waste generation in the Czech Republic. This estimate represents an expected outcome. It can thus be assumed that a larger deviation from these values will be less likely.

**Table 2** Waste generation in individual scenarios with considered probability

Scenario	Description	MMW [kt]	Bulky waste [kt]	Sorting residues [kt]	Scenario probability (%)
S1	Main prediction No cement plants restriction Landfill restriction	2694	653	444	25.0
S2	Higher separation 30% No cement plants restriction	2227	653	494	12.5
S3	Lower separation 30% No cement plants restriction	3549	653	267	12.5
S4	Main prediction 50% cement plant restriction	2694	653	444	25.0
S5	Higher separation 30% 50% cement plant restriction	2227	653	494	12.5
S6	Lower separation 30% 50% cement plant restriction	3549	653	267	12.5

#### 4.2 Computing parameters

In this section, the size of the TS-MILP model when solved for the case study is considered. The mathematical model was implemented in GAMS (General Algebraic Modelling System). The following list shows the basic parameters of the calculation.

- Number of binary variables = 180
- Number of SOS2 variables = 3,240
- Continuous variables = 143,461
- Computing time = 380 s
- Relative gap = 0%



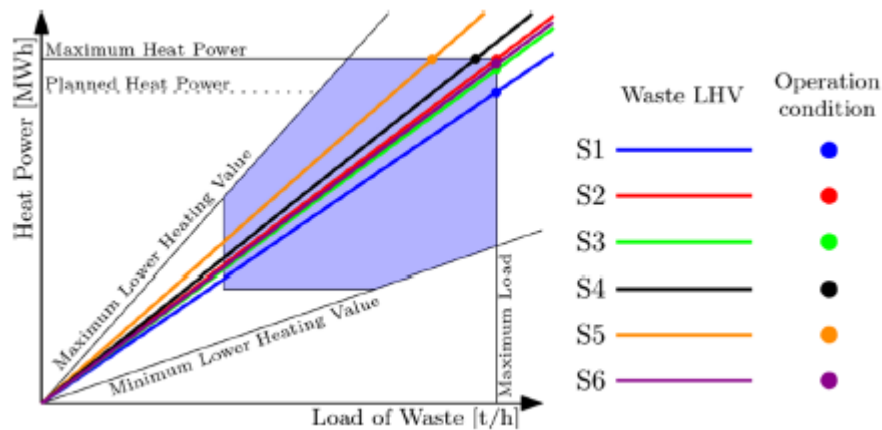


Fig. 6 LHV of incinerated waste for the selected WtE plant with a capacity of 250 kt in individual scenarios

#### 4.3 Results and discussion

In the following, the case study results are considered in detail. The locations of WtE plants are determined in the first stage of the TS-MILP model, and they are therefore identical in all the scenarios. In the second stage of the model, the waste is transported according to changes in the amounts of waste available and the LHV of the waste, to ensure acceptable operating conditions at each WtE plant. The waste composition and the LHV are different in each region, which influences the waste collection for each WtE plant. In Fig. 5, the layout of capacities and the collection areas are depicted for scenario S1.

The solution of the model proposes the construction of 14 new WtE plants with a total capacity of 1,970 kt, to support the existing four facilities with capacities of 400 kt, 240 kt, 96 kt, and 95 kt, respectively. WtE plants with large capacities are suggested by the model when they offer a better price per ton for processing waste. Small WtE plants are used to fill areas where the energy recovery from waste is considered too expensive due to long transportation distances, while the local heat demand is large. From the flows of individual types of waste, it is seen that mainly MMW and bulky waste are treated in WtE plants. Residues from recycling are used mainly in cement plants as fuel. A small amount of these residues is used in WtE plants if it is necessary to increase the LHV of the incinerated mixture. In the case of cement plant having capacity restrictions, the remaining residues are treated in WtE plants, which significantly influence the LHV of the mixture. The percentage treatment of waste in each scenario is shown in Table 3.

The treatment capacity must be sufficient for all scenarios. Therefore, the solution of each scenario is influenced by additional landfill restrictions. In the case of a decrease in MMW in scenarios S2 and S5, an increase in the percentage of waste processed in the WtE plant is evident. Conversely, in scenarios S3 and S6, excess waste from regions far away from WtE plants is landfilled. Bulky waste is used only for energy recovery due to its high LHV. Due to the lower absolute amount of waste, some residues from recycling are also used in WtE plants. It is more advantageous to increase the LHV of the incinerated mixture instead of transporting the residues over a long distance to cement plants.

The LHV of the incinerated mixture in WtE plants varies between scenarios. In general, an effort is made to keep the LHV at a high value if there is enough suitable waste. On the other hand, if sorting residues must be treated in WtE plants, the LHV can exceed the permitted limit. An example is a WtE plant with a capacity of 250 kt situated in the northwest of examined territory. Its power-throughput diagram is shown in Fig. 6.

The blue area in **Fig. 6** represents the permissible operating conditions. The WtE plant operation is mostly found in the right upper corner of the feasible area, where the mixture contains good energy potential and the facility can use its maximum capacity. A problem occurs in scenarios S4 and S5: the LHV of the mixture is too high to treat the maximum possible amount of waste. Therefore, it is necessary to redirect unprocessed waste to other facilities, and this WtE plant has reduced income from processing waste. Specifically, it is equal to 2% of annual treatment cost in scenario S4, respectively 15% in scenario S5, and it can thus affect the profitability.

Next, the individual components of the total costs and their share in the overall solution of each scenario are analyzed in detail. **Table 4** shows the individual parts of the objective function and their relative contribution. The values show that the highest cost is the treatment in WtE plants. In the case of the base scenario, almost 74% of waste is treated in WtE plants. The model reduces transportation costs by appropriately placing WtE plants within the examined territory. As a result, transportation represents about 9% of the total cost. The revenue function is negative in all scenarios. On average, all proposed WtE plants use a mixture of waste with a higher LHV than the planned value, and thus, a greater profit from the sale of heat and electricity is realized. The increased profits are not large in relative terms but would lead to a substantial annual increase in the return from investment, which can support selected projects. An important element is the losses due to unused capacity. These are unrealized gains from waste treatment caused by a too high LHV of the incinerated mixture. The average value in the case study does not represent a big loss, but there are only a few affected WtE plants, and if only these are taken into account, the losses are equal to 15% of annual treatment cost in scenario S4 and 21% in scenario S5.

The key parameters that highly influence the results are related to waste production and the calorific value of the waste. The amount of produced waste is proportional to the total cost. An increase in the waste production has greater impact than a corresponding decrease when only the landfilling waste is redirected. The landfill restriction constitutes an important aspect of the case study. Reflecting an environmental criterion, the landfill restriction, together with the economics of operation, influences the construction of new WtE facilities.

**Table 4** Costs of each part of the objective function in individual scenarios

Scenario	Treatment in WtE plant [mil. EUR]	Waste landfilling cost [mil. EUR]	Transportation cost [mil. EUR]	Revenue function [mil. EUR]	Losses due to unused WtE plant capacities [mil. EUR]
S1	304/81.0%	38.1/10.1%	43.1/11.5%	-10.0/-2.7%	0.0/0.0%
S2	304/89.7%	16.8/5.0%	34.2/10.1%	-16.2/-4.8%	0.0/0.0%
S3	304/72.9%	97.3/23.3%	31.6/7.6%	-15.8/-3.8%	0.0/0.0%
S4	300/80%	56.0/14.9%	30.9/8.2%	-16.2/-4.3%	4.1/1.1%
S5	288/81.6%	34.0/9.6%	31.1/8.8%	-16.2/-4.6%	15.9/4.5%
S6	304/73.2%	100.0/24.2%	27.1/6.5%	-16.2/-3.9%	0.0/0.0%

In a case without a landfill restriction fewer WtE plants can be expected to be built. Thus, the landfill restriction represents an additional cost for reducing emissions. Furthermore, significant changes happen in the case of restrictions on processing in cement plants. It is generally recommended not to incinerate high calorific residues in WtE plants, and when they constitute a larger share of the mixture, the entire chain becomes more expensive.

#### 4.4 Sensitivity analysis

The mathematical model contains primarily two sets of variables that influence the computing time. The first contains the binary variables  $y_i$  and the second contains the SOS2 variables  $w_{iks}$ . The number of variables of these types is determined by the number of WtE plants, and an increase in the number of variables can lead to an exponential increase in the running time of the branch-and-bound algorithm used to solve the instances. The remaining variables in the model are related to the flow of waste through the network,  $x_{e,s}$ . These variables are continuous, and thus have a smaller effect on the running time of the algorithm. The key parameters to analyze the running time of the algorithm are thus the number of scenarios and the number of WtE plants. **Table 5** illustrates results for instances with varying numbers of scenarios and potential WtE plant locations. In these runs, the optimization is stopped when reaching an optimality gap of less than 0.1%.

It can be seen that even a small increase in the number of binary variables has high impact on the solution times. The SOS2 variables can also be considered as binary variables and they are linked to the  $y_i$  variables since setting  $y_i = 0$  forces the values of the corresponding SOS2 variables.

**Table 5** Sensitivity analysis of number of scenarios and WtE plants with respect to computational demand

Solved problem	Number of binary variables	Number of SOS2 variables	Number of continuous variables	Computing time [s]
Original problem	180	3240	143,461	54
Scenarios = 10	180	5400	239,101	138
Scenarios = 15	180	8100	358,651	422
Scenarios = 20	180	10,800	478,201	1558
Scenarios = 25	180	13,500	597,750	3522
Scenarios = 30	180	16,200	717,301	5968
WtE plants = 50	250	4500	195,876	476
WtE plants = 60	300	5400	233,317	877
WtE plants = 70	350	6300	270,757	2026
WtE plants = 80	400	7200	308,197	3865
WtE plants = 90	450	8100	345,637	12,808

The results of this analysis point to the following insights should the model be applied to a different case with a different geographical structure:

- The modelled infrastructure related to sources of waste can be performed with greater detail on administrative units. Alternatively, larger territory can be investigated with more types of waste. Also, the number of scenarios can be relatively high. Increasing the number of regions where waste is produced and the number of scenarios of the model leads to a linear increase in the computational time.
- The set of potential locations for WtE plants should be carefully studied and preprocessing may be used to reduce the number of locations included when solving the model. There is an exponential increase of computing time when increasing the number of potential WtE locations.

The mathematical model is based on the real operation of WtE plants and the issues that arise as a consequence of the calorific value of waste. The results of the case study thus provide valuable information to decision makers in the real world. The benefit of the new model lies in modeling the flow both quantitatively and qualitatively. This enables the processing chain to effectively address the regions surrounding WtE plants and to negotiate possible contracts for individual types of waste. In the case of a significant deviation of the expected waste composition, the impact on economic sustainability can be quantified and adequate financial compensation can be determined to cover any losses from the reduction of the amount of incinerated waste. This can be effectively simulated using a tool built on the mathematical model by considering relevant scenarios.

## **5 Conclusion**

The presented research deals with energy recovery of waste, which is likely to be the main alternative for materially unusable waste in the future, as landfilling of waste is gradually being reduced. Waste-to-Energy (WtE) plants are costly projects with a long payback period, so it is important to include as many aspects affecting their operation as possible when making long-term plans. An essential parameter is the calorific value of incinerated waste, which is highly variable and depends on the type of waste. This study proposes a two-stage stochastic mixed-integer linear programming (TS-MILP) model describing a mixing approach for waste processing at WtE plants. It considers the heterogeneity of the incinerated waste with respect to its thermochemical properties and its effect on the WtE plants' operating conditions. The TS-MILP model aims to design a waste handling system based on a compromise between the solutions of individual scenarios while preserving the economic operating conditions of the WtE plants. The presented tool based on mathematical programming provides insights that can be used to support strategic planning and managerial decisions. It can also be used for general analyses related to a specific facility, and it is appropriate to design the facility based on the result, especially from the point of view of the operating conditions.

The developed approach was tested on a case study in the Czech Republic. Forecasted amounts and other parameters of WM were used as input data for 2030. Based on the estimated generation of waste and its calorific value, other probable scenarios were derived, reflecting either a faster fulfillment of recycling targets or a slower development due to the current pandemic. The model proposed building 14 new WtE plants with a total capacity of 1,970 kt in addition to four existing plants with a capacity of 831 kt. The suggested waste mixtures met the requirements for calorific values, and the average profits from energy sales were higher than what would have been expected from normal operations. Great attention must be paid in the case of a high LHV of incinerated waste, which significantly influences the amount of waste that can be processed and can lead to a loss of revenues. In the case of unfavorable conditions, it is possible to react appropriately by increasing the processing cost for residues already during the planning stage of a WtE plant.

Further research will focus primarily on implementing recycling dependencies to create a comprehensive tool for strategic planning. Closely related to this is the integration of environmental criteria. With the help of the presented model and the mentioned connections, a proper insight into the balance between the calorific value of waste and its material use can be provided. This study shows that in the case of a higher rate of waste separation and recycling, the operation of WtE equipment is significantly affected. In extreme cases, the system may lack the required calorific value, which may lead to the cancellation of some planned plants that will not meet operating conditions. Such projects then represent loss-making investments and must be avoided to maintain a sustainable concept of WM.

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