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# DEVELOPMENT OF AN INTELLIGENT DECISION SUPPORT SYSTEM FOR IMPROVING THE OPERATIONS OF PUBLIC UTILITY COMPANIES

**Abstract**

*The purpose of this paper is to develop and present a decision support system for improving the operations of public utility companies that deal with solid waste management. The proposed system was developed on the basis of a decision system model based on solving a limited linear optimization problem, taking into account all the specifics of the operation of public utility companies in the Republic of Serbia, which originate from the legal regulation of waste management, up to the purpose and specifics of the existence of public companies. The originality of the work is reflected in the fact that there are no similar solutions. The implementation of the proposed system will significantly contribute to the reduction of the operating costs of public companies that deal with municipal waste management.*

***Key words:*** *decision support system, waste management, public companies, Republic Serbia*

***JEL classification:*** *O31, O32.*

# РАЗВОЈ ИНТЕЛИГЕНТНОГ СИСТЕМА ЗА ПОДРШКУ ОДЛУЧИВАЊА У ФУНКЦИЈИ УНАПРЕЂЕЊА ПОСЛОВАЊА ЈАВНИХ КОМУНАЛНИХ ПРЕДУЗЕЋА

**Апстракт**

*Сврха овог рада јесте да се развије и представи систем за подршку одлучивања за унапређење пословања јавних комуналних предузећа која се баве управљањем чврстог отпада развијен. Предложени систем развијен на основама модела система одлучивања заснованом на решавању ограниченог проблема линеарне оптимизације, уз уважавање свих специфичности пословања јавних*

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*комуналних предузећа у Републици Србији, а која потичу од законске регулативе управљања отпадом, па до сврхе и специфичности битисања јавних предузећа. Оригиналност рада огледа се у чињеници да нема сличних решења. Примена предложеног система у значајној мери ће допринети редуковању трошкова пословања јавних предузећа која се баве управљањем комуналним отпадом.*

***Кључне речи:*** *систем за подршку одлучивања, управљање отпадом, јавна предузећа, Република Србија*

## Introduction

The aim of this paper is to develop an efficient Decision Support System (DSS) designed to improve the operations of public enterprises in the Republic of Serbia involved in municipal waste management, including activities such as incineration, disposal, treatment, and recycling. The treatment of waste encompasses a range of processes, such as separation, the production of refuse-derived fuel (RDF), energy recovery through incineration, organic material processing, and sanitary landfilling. According to the World Bank (2024), the global volume of solid waste amounts to approximately 2.5 billion tons, while in the Republic of Serbia, it reached about 174 million tons in 2022 (Statistical Office of the Republic of Serbia (SORS), 2024). There is a noticeable trend of continuous growth in both the quantity and complexity of waste composition, driven by the increased use of plastic and electronic products, as noted by Herva et al. (2014). This trend has led to significant concern and a heightened focus in recent years, both globally and locally, on solving issues related to solid waste management. Urbanization and population growth in cities are the main drivers of waste generation patterns and waste toxicity (Eriksson and Bisaillon, 2003, 2011; Herva et al., 2014; Emkes et al., 2015). Consequently, the treatment of solid waste has become one of the most challenging service sectors for municipal authorities in the 21st century (Zaman, 2014). Furthermore, when considering the emission of waste into air, water, and soil—posing serious risks to public health, environmental hazards both locally and globally, and socio-economic challenges (Ikhlayel et al., 201)—the issue of efficient solid waste management becomes even more critical and complex.

These complex management requirements are better controlled when supported by tools for evaluating the overall system performance, including administrative, financial, legal, and planning aspects (Mendes et al., 2013). According to Eriksson et al. (2003), the main advantages of waste management models lie in their ability to handle complexity and uncertainty. Therefore, the development of appropriate systems based on modern ICT for solid waste management is essential. One potential solution is the development of a Decision Support System (DSS). The primary goal of a DSS is to plan municipal waste management, define the waste flows that need to be directed toward recycling or various treatment and disposal facilities, and propose the optimal number, types, and locations of facilities that need to be operational. A specific goal of the research is to develop a software solution that will enable the effective implementation of the model.

The idea is to develop a DSS as a decision-making system based on solving a constrained nonlinear optimization problem using two types of variables: binary and continuous. This approach would rely on the use of a genetic algorithm for optimization, as such an algorithm can efficiently handle different types of variables and return an optimal solution regardless of the starting point. The objective function would take into account all possible economic costs, while the constraints would arise from technical, regulatory, and environmental considerations. For this purpose, a linear or quadratic optimization model can be used. Thus, the combination of genetic algorithms with optimization techniques can be an effective approach to solving complex decision-making problems in the field of waste management. Simply put, the decision-making model must consider all factors significant for making decisions related to waste management, ensuring that the outcome is a decision that minimizes total costs while addressing all aspects of waste management and adhering to constraints arising from technical, regulatory, and environmental issues. For example, technical constraints relate to the capacity of waste treatment facilities, the technology used, and similar factors. Regulatory constraints include legal regulations and standards that must be met during waste management. Environmental constraints relate to protecting the environment and minimizing negative impacts on the surroundings.

Therefore, the aim of this paper is to develop a decision-support model that accounts for both environmental and economic aspects of waste management in local governments. The application of this approach will enable the modeling and analysis of a heterogeneous set of subsystems affected by decisions related to solid waste management. By integrating all subsystems into the decision-making process, it will be possible to make optimal decisions regarding the size and typology (e.g., separators, incinerators, etc.) of various treatment facilities, based on a detailed analysis of waste composition. Ultimately, this will result in improved operations of public utility companies in the Republic of Serbia.

## Literature review

In recent years, numerous papers can be found that have the development of solid waste management models as their subject. Most of these models are based on decision support models. The basic idea behind the authors of these papers in developing the model is to create an optimal trade-off between reality and the computational complexity of the model. In other words, they are guided by the requirement that the model reflects the real situation as realistically as possible, without being too complex for data processing. Since solid waste management in urban areas represents a very complex problem that includes various aspects of the functioning of society, starting from economic and technical issues, up to compliance with human and environmental protection standards, the development of a model that will reflect the optimal trade-off between reality and computational complexity represents a very difficult task. Therefore, it is not surprising that many authors have not been successful in achieving this requirement.

The consequence of the above mentioned is that the authors have mainly focused on one aspect of the functioning of a society due to the fact that solid waste management, from its generation to final treatment, is very complex (Chen & Wang, 2017). In addition, it should be added that solid waste management is further complicated by the lack of awareness and community participation, the mind set and commitment of staff, the lack of improved collection equipment, the lack of human resources, the lack of landfill land, inexperienced operation and maintenance of the landfill, financial constraints, staff training, the shortage of basic studies and insufficient data on solid waste, etc. (Santibanez-Aguilar et al., 2017). For this reason, as a rule, many authors have focused on the development of economically based optimization models for the allocation of municipal waste streams. The first such model was presented by Chang & Chang (1998). The model is based on the minimization of the total costs of waste management. The minimization of the objective function is achieved by solving a constrained nonlinear optimization problem. The cost function includes the costs of transportation, treatment, maintenance and recycling and takes into account the possible benefits from the sale of electricity. However, the main drawback of this model is that it does not take into account other aspects of society, such as environmental protection, as well as technological aspects of waste treatment. Based on this model, Fiorucci et al., (2003) developed a similar model, which takes into account different classes of constraints, such as regulations on minimum recycling requirements, incineration process requirements, landfill conservation and mass balance. However, the cost function which should be minimized only includes the costs of recycling, transportation, and maintenance.

It can be stated that a large number of studies focusing solely on the economic criterion, primarily the selection of the optimal location for an inter-municipal landfill, are based on the application of AHP and fuzzy methods. Such models were presented by Afzali et al. (2014), Kahraman et al. (2017), Kharat et al. (2019), Rani et al. (2021), Das et al. (2022), Kabir et al. (2022), Musart et al. (2022), Demircan and Yetilmezsoy (2023), Aghad et al. (2024), Kang et al. (2024), Sadati et al. (2024), Shukor et al. (2024), and others. However, an approach based solely on economic considerations cannot be considered fully satisfactory when addressing waste management issues. In fact, a broad range of potential developments must be considered. Above all, modeling the impact of solid waste management on the environment requires modeling and analysis of a fairly heterogeneous set of subsystems influenced by decisions related to solid waste management. In this context, multi-criteria decision models are effective because they allow decision-makers to assess existing or potential alternatives while simultaneously considering and applying multiple conflicting criteria (Belton & Stewart, 2002; Kou et al., 2011; Zhou et al., 2010). Due to their ability to process several criteria, these models are considered highly efficient for decision support in solid waste management (Soltani et al., 2015). Based on this, the model presented by Garcia-Garcia (2022) represents an attempt to incorporate a greater number of social aspects and utilization. However, the main drawback of this model is that it does not cover all relevant aspects of society and relies on simple techniques of the Analytical Hierarchy Process (AHP) (multi-criteria decision-making). A similar model, integrating more sustainability criteria in waste management, was presented by Torkayesh et al. (2022). Their model includes environmental, social, and economic criteria and is based on a combination of multi-criteria decision-making models and life cycle assessment models that evaluate the sustainability of waste management systems. However, the model does not include the technical-technological aspects of solid waste management.

The most comprehensive solid waste management model currently available is presented by Shaban et al. (2022). The authors developed a generic optimization model suitable for developing an efficient solid waste management system in developing countries. A mixed-integer linear programming model has been formulated for a solid waste management system configuration that integrates waste generation sources, collection/transfer stations, recycling facilities, incineration plants, and landfills. The proposed model is designed to determine the optimal number and locations of various facilities, as well as the optimal waste flow within the system, aiming to minimize the net daily costs incurred by the system. However, the model does not incorporate legal regulations. A similar model was presented by Ahani et al. (2019), Anwar et al. (2018), and Youseflоо & Babazadeh (2019).

In recent years, with the development of machine learning (ML) and artificial intelligence, an increasing number of researchers have focused on developing IT-based models for waste management. This is because the quantification and prediction of solid waste play a vital role in the efficient planning of solid waste management systems (Singh & Satija, 2017). The application of neural networks, as opposed to traditional statistical analysis techniques, enables effective analysis of sophisticated nonlinear functions in multidimensional spaces (Kannangara et al., 2017), providing a solid foundation for analyzing the multidimensional problem of waste management. Similar perspectives are shared by Younes et al. (2015) and Yusoff et al. (2018). Therefore, this approach offers a strong basis for studying issues such as solid waste management (Jalili & Noori, 2004; Ponce, 2004; Kurtulus et al., 2006; Yamin et al., 2008; Noori et al., 2010; Oliveira et al., 2018), despite the fact that predicting solid waste remains uncertain due to the dynamic and unpredictable nature of social, economic, and demographic factors (Chhay et al., 2018). Furthermore, accelerated economic development and urbanization add to the already complex nature of solid waste (Shams et al., 2017). Hoque et al. (2020) utilized artificial intelligence to predict landfill surface area based on solid waste collection forecasting. Meza et al. (2019), Camero et al. (2019), and Kulisz and Kujawska (2020) focused on predicting solid waste quantities, while Batinić et al. (2011) used AI to predict waste characteristics. Gue et al. (2022) developed a machine learning model based on rule-based analysis to evaluate the impact of city and country attributes on waste management. Unfortunately, their model identified local governance and technological research as key attributes influencing sustainable waste management but did not offer strategies for managing waste at the enterprise level under local government jurisdiction, either directly or indirectly. A similar effort was presented by Mishra et al. (2022), who introduced a Smart Waste Management Model. This model combines the concepts of the Internet of Things (IoT) and artificial intelligence. The core idea of their model is to leverage the predictive capabilities of AI-based models and apply these advantages in automated decision-making. However, their model focuses solely on prioritizing bin emptying decisions rather than addressing the entire waste management flow at the local governance level. The idea for their model was inspired by works of various authors, such as Alizadeh et al. (2018), Ayeleru et al. (2021), and Fan et al. (2022a, b), who used neural network models to solve specific problems in urban management. Among the pioneers using neural network models based on multi-layer perceptron (MLP) for waste management were Alidoust et al. (2021) and Lin et al. (2022). The model developed by Lin et al. (2022) is particularly noteworthy because it incorporates criteria related to storage, transportation, and disposal of waste into the decision-making process. Alidoust et al. (2021) used their model for modeling physical properties of waste, while Ayeleru et al. (2021) applied it for quantity prediction. A notable challenge with ML models is their limited interpretability for decision-makers (Rudin, 2019). Rule-based "if-then" systems, on the other hand, allow for easier subjective interpretation because causal relationships are inherently expressed in linguistic form (Gue et al., 2022).

However, regardless of the purpose for which neural network models are used in solid waste management, a common issue is that the model's performance depends on the historical length and quality of the data (Masebinu et al., 2017). Supporting the use of neural networks are the findings of Sun and Chungpaibulpatana (2017), who demonstrated that artificial neural networks (ANN) provide highly accurate predictions of waste generation. They also highlighted that influential factor such as total population, age, number of households, household income, and similar variables significantly contribute to waste generation. Similar arguments supporting the use of neural networks have been presented by Abdoli et al. (2011), Shahabi et al. (2012), Antanasijević et al. (2013), Shamshiry et al. (2014), Azadi and Karimi-Jashni (2016), and Abbasi and Hanandeh (2016).

The increase in municipal solid waste (MSW) generation has become not only a significant sustainability challenge but also a major financial burden for municipalities worldwide. Therefore, it is insufficient to focus solely on waste quantity prediction; it is equally important to involve the public in the waste management process, as they are key stakeholders. This has led to the development of a second group of waste management models that incorporate public participation in decision-making processes. These models aim to achieve a compromise among stakeholders, given that conflicts often arise from the complex network of stakeholder values. Such conflicts can impact the feasibility of implementing any decision (Ananda et al., 2003). Models of this kind have been presented by Hung et al. (2006), Morrissey and Browne (2004), and Wilson et al. (2001). These models are typically based on a combination of multi-objective programming methods and multi-criteria decision-making approaches. The primary drawback of these models lies in determining the degree of consensus required among stakeholders. As a result, their application in municipal-level solid waste management remains debatable.

Few studies have focused on the development of ICT-based decision support systems (DSS) for solid waste management in local governments. Decision support systems are valuable tools that assist managers in ensuring compliance with solid waste management regulations proposed by governments. Pires et al. (2011) and Souza Melaré et al. suggested that DSS can be developed using ICT and optimization algorithms. Building on these ideas, it is possible to develop an ICT-based decision support system that would be effective in public enterprises in the Republic of Serbia engaged in solid waste treatment. Despite the fact that various stakeholders are involved in solid waste management in the Republic of Serbia, each with different concerns and criteria encompassing economic, environmental, political, and social aspects, an efficient system can be developed. Such a system would allow for the classification and analysis of alternative solutions while respecting the wide range of conflicting criteria. In developing the system, a systemic approach will be adopted, as proposed by various authors, including Staples and Niazi (2008), Kitchenham and Charters (2007), Guessi et al. (2011), and Souza Melaré et al. (2017).

## Model Development and object function

The model development assumes that urban planning documents in the municipalities of the Republic of Serbia have designated locations for the construction of certain types of facilities. Since these facilities may or may not be built, binary variables are introduced into the model (whether they will be built or not). Therefore, the problem of making optimal decisions is reduced to solving an optimization problem with nonlinear functions and integer decision variables.

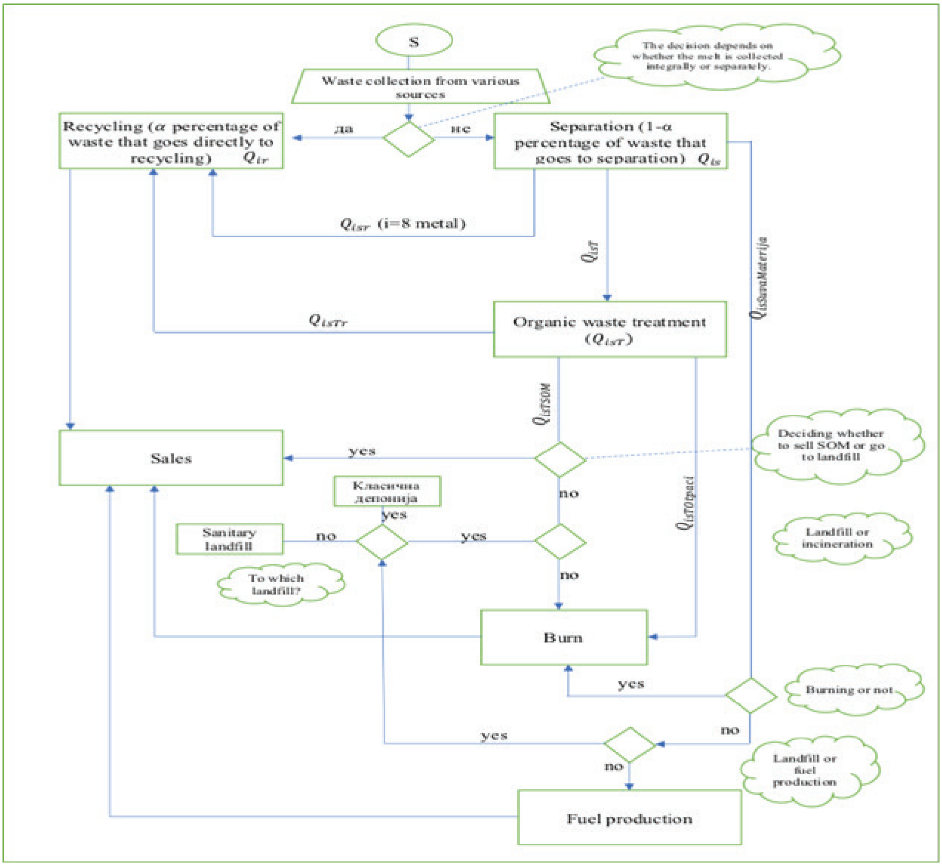
The first step in model development is to consider the process of solid waste treatment. Given that the Republic of Serbia is aligning its regulations with those of the European Union, the model is based on the classification of solid waste as prescribed by the EU. According to EU regulations, solid waste is classified into 11 categories: 1 - paper, 2 - heavy plastic, 3 - plastic bags, 4 - plastic bottles, 5 - glass, 6 - organic, 7 - wood, 8 - metals, 9 - residual waste, 10 - inert materials, and 11 - textiles. It is noted that for each waste category, the calorific value of the waste before and after any treatment is determined based on the chemical composition of the waste. Daily quantities of waste are collected from various locations, with only 9 categories of waste being recyclable, and they can be collected either separately or partially separated (paper, heavy plastic, plastic bags, plastic bottles, glass, organic waste, wood, metals, and textiles). The collected waste undergoes separation, with the separation process depending on the method of collection. The remaining waste, which is collected without separating different materials, is sent for further separation, landfill, or incineration. From the separation process, three types of sorted waste can emerge:

- Metals, which are sent for recycling.
- Organic materials (wet waste), which undergo further treatment:
  - Organic material sent for recycling is used for compost production.
  - Wet material is processed in an organic waste treatment facility, resulting in stabilized organic material (SOM) and residues. SOM can be sold, incinerated in a waste-to-energy facility, or sent to a landfill, while the residues are directly sent to the landfill.
- Other materials (dry waste), which can be incinerated, sent to a facility for fuel production, or disposed of in a landfill.

It is important to note that recycling alters the composition of waste sent for incineration. This means that its calorific value changes after recycling, and consequently, the energy recovery value from waste incineration is also affected. This data is taken into consideration due to the positive benefits of energy recovery through waste incineration. The material sent to the landfill can be directed to either a conventional landfill or a sanitary landfill, with the quantity of waste disposed of being limited by the maximum flow of municipal solid waste that can be sent to the landfill, or equivalently, by the minimum number of years required to completely fill the landfill.

In addition to the aforementioned specifics, the model development takes into account the possibility of multiple locations for each type of facility, including separation, incineration, recycling, landfills, and waste treatment. This means that indicators can be assigned to each facility to handle a specific quantity and type of waste. The existence of different locations increases the waste treatment costs. This concept can be best represented graphically, as shown in Figure 1.

**Figure 1. Waste treatment model in public utility companies (PUC)**




Note: $Q_{i,R}$ – Quantity of waste of the i-th material that is directly recycled; $Q_{i,S}$ – Quantity of waste of the i-th material that goes to separation; $Q_{i,S,R}$ – Quantity of waste of the i-th material that goes from separation to recycling (metals, i=8); $Q_{i,S,T}$ – Quantity of waste of the i-th material that goes from separation to treatment; $Q_{i,S,T,\,SOM}$ – Quantity of waste of the i-th material from treatment representing stabilized organic material (SOM); $Q_{i,S,T,\,waste}$ – Quantity of waste of the i-th material from treatment representing waste; $Q_{i,S,T,\,Sum\ of\ Materials}$ – Quantity of waste of the i-th material that does not go to treatment from separation due to being dry material and directly goes to either the incinerator, landfill, or fuel production.
Source: Authors

The decision variables related to separation would be: $\psi_s^p$, $\psi_{r\varphi}$, $\psi_i^n$, $\psi_l^m$, and $\psi^t_l$. Similarly, variables for landfills, fuel production, waste treatment, and incineration would be defined. Binary variables would refer to all these facilities to describe whether they exist or not, and they would be coded as 1 for existence and 0 for non-existence. Thus, we get: Sp – indicator for the p-th separator (p = 1…P), Rq – indicator for the q-th fuel production facility (q = 1…Q), In – indicator for the n-th incinerator (n = 1…N), Lm – indicator for the m-th landfill (m = 1…M), Tl – indicator for the l-th organic waste treatment facility (l = 1…L).

Considering the described solid waste treatment process, as well as all the listed constraints, the cost function encompasses all costs, from collection costs, placement, and procurement of various types of containers, to waste recycling. For example, transportation costs represent a function of the number of vehicles (maintenance and fuel costs), employee wages (which depend on the number of trips required for waste transport and the number of trips one driver can make during their working day), and variable costs determined by the distance between different facilities and waste collection points. Therefore, transportation costs can be represented as follows:

$$C^{T} = \sum_{(s,d)\in X} \frac{\hat{Q}_{s,d} c_{s,d}}{V_{s,d}} \qquad (1)$$

The following symbols represent:

| | | |
|---|---|---|
| $X$ | - | *Set of possible connections between two facilities* |
| $s,d$ | - | *Connection between two facilities* |
| $C_{s,d}$ | - | *Transportation costs between facilities* |
| $\hat{Q}_{s,d}$ | - | *Quantity (volume) of waste transported between facilities on an annual basis* |
| $V_{s,d}$ | - | *Capacity of a single vehicle for waste transportation used on the route between two facilities* |

The second group of costs consists of installation and maintenance costs of the facilities. These costs include a fixed component $CF$ and a variable component $CV$. The fixed cost depends on the decision of whether the facility is included in the system or not and is incorporated into the cost function. This is an integer decision. For example, a decision of 1 means that the facility is used and the fixed cost is included in the cost function. If the decision is 0, the facility is not included and the fixed cost does not contribute to the total cost function. This represents a cost proportional to the amount of material processed by the facility during the year. Therefore, the larger the amount of material entering the facility, the higher the cost will be. The variable cost is calculated as the product of a coefficient (representing the cost per unit mass) and the mass of waste entering the facility. Thus, the installation and maintenance costs of the facility can be represented as:

$$C^{m} = \sum_{p=1}^{P} \sum_{i=1}^{D} Q_{p,i} * price_{i} + \sum_{p=1}^{P} C_{F} \qquad (2)$$

The final group consists of recycling costs. These represent a function of different types of separation methods, where the selected method represents the best solution for a given amount of a specific type of waste. Thus, we obtain $xi,j$, where x is the portion of waste of the i-th material obtained by applying the j-th method. The idea is to consider these proportions as fixed parameters, justifying the fact that, in every case, the most economical waste separation method is chosen, which corresponds to the needs of the local government (urban structure, socio-economic characteristics of the population, etc.). Thus, the recycling costs on an annual basis can be represented as:

$$C^r = \bar{n} \sum_{i=1}^{11} \left( \left( \sum_{j=1}^{4} C_{i,j}^{x} r_i \alpha_i x_{i,j} \right) - B_i r_i \alpha_i \right) \quad (3)$$

The following variables represent:

$C^R$ - the cost per unit weight of waste per day

$B_i$ - the economic benefit from the sale of the i-th material in the amount of $ri\alpha i$

n̄ - the average number of' days

j - ranges from 1 to 4, as there are 4 types of recycling techniques

Given that there are economic benefits from recycling, both in terms of revenue generated from the sale of recycled materials and from the sale of thermal and other energy, the objective function must incorporate a utility function before the cost functions. Taking into account all potential economic benefits from waste treatment, the function would look as follows:

$$B = \sum_{q=1}^{Q} price_{rec.mat} RM_q + \sum_{n=1}^{N} \tilde{c}_e \left( \frac{\eta_E HV_{I_n} \bar{n}}{f} - E_{c,n} \right) \quad (4)$$

Where the following represent:

$$RM_q = \bar{n} \sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{i=1}^{11} (1-\alpha_i) r_i \chi \, P_{d,i} \Phi P_{d,} S_p (1-k_i) \times (1-\eta_i) \psi S_{p,} C_q \, (1-\hat{\eta}_i) \Theta_{S_p,C_q} \quad (5)$$

$\tilde{C}_e$ - *unit price [E/kWh] for energy sales;*

$E_{c,n}$ - *annual energy consumption [kWh/year] for the n-th incineration unit;*

$\eta_E$ - *efficiency related to energy production in relation to the heat generated by combustion;*

$ff$ - *conversion factor, equal to 3.6 MJ/kWh;*

$HV_{In}$ - *total daily thermal energy of waste entering the n-th incineration unit.*

Considering the above, we obtain the following objective function:

$$C = C^t + C^m + C^R - B \quad (6)$$

Since regulations dictate that certain types of waste cannot be collected together and that specific methods must be applied in their treatment, constraints regarding the waste structure (compliance with mass balance equations), space size, etc., such constraints are described as regulatory constraints. Mathematically, they can be represented as follows, with Z representing the percentage corresponding to the prescribed minimum amount of waste that must be recycled, according to the law in the Republic of Serbia.

$$\sum_{i=1}^{11} \alpha_i r_i + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{11} k_i(1-\alpha_i) r_i \chi\, P_{d,i}\, \Phi P_{d,} S_p + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{11}\sum_{s=1}^{S}(1-\alpha_i)\, r_i \chi\, P_{d,i} \Phi P_{d,} S_p (1-k_i)\eta_i\, \tilde{\eta}_i\, \gamma T_{s,} M$$
$$+ \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{11}\sum_{q=1}^{Q}(1-\alpha_i)\, r_i \chi\, P_{d,i} \Phi P_{d,} S_p (1-k_i) \times (1-\eta_i)\psi S_{p,} C_q (1-\hat{\eta}_i)\Theta_{C_{q,}M}$$
$$\geq Z \sum_{i=1}^{11} r_i \; (7)$$

The following symbols represent:

$k_i$ - *the fraction of material i that is sent for recycling after separation;*

$\eta_i$ - *the fraction of material i, relative to the total material not recycled after separation, that is sent (as wet material) for biological treatment;*

$\tilde{\eta}_i$ - *a parameter representing the fraction of material i that enters the biological treatment facility and remains in the stabilized organic material; note that the dependence of this fraction depends on index i because cleaning operations to remove residues take place in the biological treatment plant, with an efficiency that also depends on index i;*

$\hat{\eta}_i$ - *the fraction of material i that enters the RDF (Refuse Derived Fuel) facility and remains as a component of the RDF produced in that facility; again, this fraction depends on index i.*

The second group of constraints consists of technical constraints. These are typically limitations related to the amounts of material that can be received, delivery times, raw material quality, and ecological and safety standards that must be adhered to. In solid waste management, such constraints apply to the daily intake of material into incinerators, separators, organic material treatment plants, and fuel production plants. More specifically, the amounts of waste entering these facilities must lie between certain fixed values, which can be mathematically represented as follows:

$$\mathrm{M}_{I_{n,a}}\delta_{I_n} \leq Q_{I_n} \leq \mathrm{M}_{S_{p,b}}\delta_{I_n} \qquad (8)$$
$$\mathrm{M}_{S_{p,a}}\delta_{S_p} \leq Q_{S_p} \leq \mathrm{M}_{S_{p,b}}\delta_{S_p} \qquad (9)$$
$$\mathrm{M}_{C_{q,,a}}\delta_{C_q} \leq Q_{C_q} \leq \mathrm{M}_{C_{q,b}}\delta_{C_q} \qquad (10)$$
$$\mathrm{M}_{\mathrm{T}_{s,,a}}\delta_{T_s} \leq Q_{C_q} \leq \mathrm{M}_{\mathrm{T}_{s,b}}\delta_{T_s} \qquad (11)$$

In addition to this constraint, the model also includes a constraint related to the conservation of mass. This constraint can be represented by an equation that ensures the mass of material entering the system is equal to the mass of material leaving the system, plus the mass retained within the system, or mathematically, F_{\text{in}} - F_{\text{out}} = \Delta mass. This constraint occurs at every branching point where the waste flow can be split. Regardless of the branching point, the general constraint can be expressed as the difference between the flow of material entering and exiting the facility being equal to the change in mass within the system over a specific time period.

Since the treatment of solid waste involves the presence of certain facilities when a specific type of solid waste is present, the decision regarding their presence or absence must also be included in the model. The constraint is that when the amount of a specific type of waste is greater than zero, the corresponding facility must be present, or mathematically: P = \text{sgn}(F_{\text{in}}).

The third group of constraints pertains to environmental standards. In the context of solid waste management, they relate to the chemical content of fuel and SOM (stabilized organic material). In the case of fuel production, these constraints address the chemical characteristics of the fuel in order to minimize ash, Cl, S, moisture, as well as its calorific value, which can be mathematically represented by the following constraint:

$$\sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{11} k_i(1-\alpha_i)r_i\chi\, P_{d,i}\ \Phi P_{d,}S_p(1-k_i)\times(1-\eta_i)\psi S_{p,}C_q(-\hat{\eta}_i)\mathrm{A}_i \geq 0 \quad (12)$$

Where Ai is defined by specific constraints related to heat, Cl and S concentration, moisture, and ash content. Similarly, the constraint related to SOM (Stabilized Organic Material) is defined, concerning the concentration of plastics, pH values, and emissions of unpleasant odors.

$$\left\{\sum_{d=1}^{D}\Phi P_{d,}S_p\,\beta_{S_p,T_s}K\right\} - H\left\{\sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{i=1}^{11}(1-\alpha_i)r_i\ \Phi P_{d,}S_p\,(1-k_i)\eta_i\beta_{S_p,T_s}\hat{\eta}_i(1-h_i)\right\} \quad (13)$$

Given that K and H are constants, hi refers to the moisture content in material i-th after stabilization.

The emission limits from the incinerator related to sulfur oxides, hydrochloric acid, nitrogen oxides, heavy metals, and dust are given by the following expressions: [E_{\text{SOx}} \leq C_{\text{SOx}}^{\max} ] Where (E_{\text{SOx}}) represents the total sulfur dioxide emissions from the facility, and (C_{\text{SOx}}^{\max}) is the maximum allowed concentration of SOx in the flue gas; [ E_{\text{HCl}} \leq C_{\text{HCl}}^{\max} ] In which (E_{\text{HCl}}) represents the total emission of HCl, and (C_{\text{HCl}}^{\max}) is the maximum permitted concentration of HCl: [ E_{\text{HF}} \leq C_{\text{HF}}^{\max} ] In which (E_{\text{HF}}) represents the total emission of HF, and (C_{\text{HF}}^{\max}) is the maximum permitted concentration of HF; [ E_{\text{NOx}} \leq C_{\text{NOx}}^{\max} ] In whch (E_{\text{NOx}}) represents the total emission of nitrogen oxides, and (C_{\text{NOx}}^{\max}) is the maximum permitted concentration of Nox; [ E_{\text{heavy\ metals}} \leq C_{\text{heavy\ metals}}^{\max} ] In which (E_{\text{heavy\ metals}}) represents the total emission of heavy metals, and (C_{\text{heavy\ metals}}^{\max}) is the maximum permitted concentration of heavy metals; [ E_{\text{dust}} \leq C_{\text{dust}}^{\max} ] in which (E_{\text{dust}}) represents the total dust emission, and (C_{\text{dust}}^{\max}) is the maximum permitted dust concentration.

Since sanitary landfills are not environmentally sustainable over a long period, the model must include a limitation on their saturation. Since such a limitation can be expressed in terms of the minimum filling time, this constraint can be mathematically written as follows: $\hat{}\hat{Q}_{I_n,L_m}+\hat{Q}_{P_d,L_m}+\hat{Q}_{S_p,L_m}+\hat{Q}_{som,L_m}+\hat{Q}_{T_s,L_m}+\hat{Q}_{C_q,L_m} \leq \frac{V_{Lm}}{T_{Lm}}$, where $V_{Lm}$ is the amount of waste that saturates the landfill, and $T_{Lm}$ is the time it takes for the landfill to reach saturation.

## Conclusion

The developed model in this paper represents an efficient decision support system (DSS) for improving the operations of public utility companies in the Republic of Serbia. It is essential for optimizing municipal waste management, as well as for integrating recycling and waste disposal. The model is developed based on the formalization of a constrained nonlinear optimization problem, where some decision variables are binary, while others are continuous. The objective function encompasses all potential economic costs, while the constraints are based on technical, regulatory, and environmental aspects. In general, this approach allows for the exploration of various aspects that are important for planning a municipal waste management system. Special emphasis is placed on the precise characterization of the system in terms of the chemical composition of waste, calorific value, material recovery, and available treatment methods. Attention is also given to environmental impacts.

However, like any model, this one also has several shortcomings. The first drawback concerns the complexity of the model. The model contains many variants and functions, including binary and integer variables. This complexity may complicate analysis and implementation, as well as require robust software for solving. Although it is mentioned that the functions are nonlinear, certain assumptions about linearity in the optimization problem may reduce the accuracy of the model. For example, factors such as transportation costs, which may behave nonlinearly as a function of distance, may not be accurately modeled. The model must adapt to constantly changing laws and regulations, which may make its long-term use difficult. If new laws become stricter concerning certain types of waste, the model may not be sufficiently adaptable. Many types of waste are interrelated. For example, recycling one material (e.g., plastic) can affect the availability and processing costs of another material. This interdependence may not be adequately modeled. The waste treatment process is dynamic, with seasonal variations in the quantity and type of waste. The model may fail to capture the timing of these variations and may not easily adjust to changes or events. Additionally, the market for recycled materials and energy can be unstable and subject to fluctuations. This can affect the profitability of the solutions proposed in the model and significantly reduce the attractiveness of certain waste treatment methods.

In summary, while the proposed model offers a comprehensive approach to solid waste management, considering various relevant aspects, it possesses several limitations that could impact its effectiveness and practical implementation. It is recommended that further verification and sensitivity analysis be conducted, and that the model be integrated with empirical data and practical experience to enhance its applicability and contribute more effectively to addressing the challenges of waste management.

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## Apendix

- For the purposes of this work, the limits are set to the following values;
- (g \cdot HVi - 3600 \text{ kcal/kg}), where are:
  - **(HVi)**: Heating value for (i) type of material in MJ/kg.
  - **(g)**: The conversion factor used to convert MJ into kcal, given as (238.9 \text{ kcal/MJ}).
  - Thus, the limitation is imposed that the heating value for a given material must be above (3600 \text{ kcal/kg}).

**2. Restriction regarding chloride content (Cli)**

- Another limitation refers to the chloride content in the produced RDF, which must be less than (0.9%).
  - (0.009 - Cli): This expression ensures that the chlorophytic content for the (i)th type of material is less than (0.009) (or (0.9%)).

**3. Sulfur (Si) content limit**

- The third limitation refers to the sulfur content:
  - **(0.006 - Si)**: As with chlorine, this limit ensures that the sulfur content of the RDF is less than (0.6%) ( (0.006)).

**4. Ash content limitation (Ashi)**

- The fourth limitation refers to the ash content:
  - **(0.002 - Ashi)**: This limit ensures that the ash content of RDF is less than (0.2%)