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EVALUATING THE LANDFILL LEACHATE QUALITY USING LEACHATE POLLUTION INDEX (LPI) AND TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO AN IDEAL SOLUTION (TOPSIS)

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ABSTRACT: Variability and diversity of landfill leachate cause difficulties in assessing the actual degree of threat to the environment and selecting an appropriate method of disposal or treatment. Therefore, quantifying leachate contamination potential is essential in landfill management and could be used to assess the accuracy of landfill operation and its impact on surrounding areas. The aim of this paper was to evaluate the performance of the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method and its suitability in determining leachate pollution potential in comparison to the Leachate Pollution Index (LPI) method. For this purpose, the quality of leachate from the landfill, collected four times a year from 2004 to 2021, was analysed. The following parameters were monitored: pH, EC, Pb, Cu, Zn, Cr, and Hg. On the basis of the measured parameters, the LPI and TOPSIS indexes were calculated. The obtained results indicated that the TOPSIS method is more sensitive and accurate in observing changes in leachate quality. It can be applied to any number of contaminant parameters without restrictions on scope, quantity, or their relative importance. It can also be used to compare the variations in leachate quality over time or to analyse differences in leachate quality among various landfill sites.

KEYWORDS: landfill, leachate quality, Leachate Pollution Index, TOPSIS

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Introduction

Sanitary landfills are widely practised methods of waste disposal in both developed and developing countries (Manaf et al., 2009; Rajoo et al., 2020). According to the World Bank, globally, 69.6% of waste is currently dumped on: controlled landfills (3.7%), unspecified landfills (25.2%), sanitary landfills with gas collection (7.7%) and open dumps (33%) (Kaza et al., 2018).

In European Union countries, an average of 32.3% of municipal waste went to landfills in 2020 (Eurostat, 2022). One of the inevitable consequences associated with the operation of landfills is the generation of leachate. It is generated both during operations and many years after the closure of landfills as a result of rainwater infiltration and seepage through waste layers (Aziz et al., 2010; Wdowczyk & Szymańska-Pulikowska, 2021). Variation in leachate composition is often attributed to the volume of water that infiltrates into the landfill as well as to the physico-chemical and biological process taking place in the waste body (Kulikowska & Klimiuk, 2008; Długosz, 2012; Teng et al., 2021).

Due to the diverse nature of landfilled waste, leachates constitute a variety of pollutants and can seriously pollute groundwater and other water bodies (Rajoo et al., 2020; Hussein et al., 2019; Nyirenda & Mwansa, 2022). Thus, leachate monitoring should be the priority factor that is considered in the operation and long-term management of municipal landfills (Wdowczyk & Szymańska-Pulikowska, 2021; Długosz, 2012). Variability and diversity of landfill leachate cause difficulties in assessing the actual degree of threat to the environment and selecting an appropriate method of disposal or treatment. Therefore, understanding and quantifying leachate contamination potential is essential in landfill operations and management. According to Adhikari et al. (2020) and Abunama et al. (2021), quantifying leachate contamination potential could be used for evaluation of the accuracy of landfill operation/exploitation and its impact on surrounding areas.

An overview of the literature

One of the possibilities for leachate quantification is Leachate Pollution Index (LPI), proposed by Kumar and Alappat (2005a, 2005b). It is an the environmental index used as a quantitative and comparative measure to quantify pollution potential of leachate generated at landfills (Lothe & Sinha, 2017; Hussein et al., 2019). The LPI is a single number that expresses the overall leachate contamination potential of a landfill based on several leachate pollution parameters at a given time. It is an increasing scale index where in a higher value indicates a poor environmental condition (Agbozu et al., 2015; Hussein et al., 2019). It is used in many environmental studies to assess landfill leachate contamination in Europe (Tałałaj, 2013; Wdowczyk & Szymańska-Pulikowska, 2021), Asia (Kale et al., 2010; Umar et al., 2010; Munir et al., 2014; Bhalla et al., 2014) and others continents (Godwin & Oghenekohwiroro, 2016).

In addition to the LPI, several cluster analysis and multivariate statistical techniques have been used over physicochemical data of leachate analysis to evaluate leachate contamination potential (Ergene at al., 2022; Adelopo et al., 2018; Boateng et al., 2018, Mishra et al., 2016; Mishra et al., 2019). These statistical approaches can be used to show significant similarities and differences between leachate samples and different landfills. Findings of multivariate analysis may also supply information about the specific properties of landfill leachate as well as its sources (Ergente et al., 2022).

Numeric methods, such as artificial neural networks (ANNs), have been used to predict leachate quantity and quality (Ishii et al., 2022; Abunama et al., 2019; Azadi et al., 2016). According to the studies conducted, ANNs provided good results in the modelling of leachate generation efficiency (Ishii et al., 2022). It can also be applied for the prediction of pollutant removal efficiency from landfill leachate (Arabameri et al., 2017; Masouleh et al., 2022).

In recent years, Multicriteria Decision-Making (MCDA) methods have gained importance as a potential tool for landfill exploitation and management. They seem to be an intelligent system that utilises and converts spatial and non-spatial data into valuable information and accuracy (Dolui & Sarkar, 2021). In this study, one of the MCDA methods – Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) was used to determine the landfill pollution potential. The method evaluates and ranks the best alternative that is close to the ideal solution and furthest from the negative one (Dolui & Sarkar, 2021). Similar to LPI method, the result of TOPSIS analyse is a single value, thus it can express the overall leachate pollution potential.

There is not much data in the literature on the feasibility of TOPSIS to assess landfill leachate quality. Available studies refer to the security of urban water supply (Yang et al., 2023), health risk for municipal solid waste (Singh & Kumar, 2022), performance of municipal wastewater treatment plants (Guruprasad et al., 2018), municipal solid waste (Mir et al., 2016), improve municipal solid waste planning and forecasting (Estay-Ossandon et al., 2018), treated wastewater instream in an urban watershed (Kim et al., 2013), selecting municipal solid waste treatment (Roy et al., 2019; Martowibowo & Riyanto, 2011).

In the context of the information presented, the purpose of this study is to evaluate the performance of TOPSIS method and its suitability in determining leachate pollution potential in comparison to LPI method.

The originality of the study lies in the evaluation of TOPSIS performance compared to the result of the LPI method, which has not been described in the literature so far. Thus, the application of TOPSIS can be considered as another novelty of the conducted study. Additionally, assessing the leachate quality to demonstrate its pollution range seems to be a practical implication of presented analyses.

Research methods

Material

The leachate samples were collected from a municipal landfill in northen-easter Poland. The landfill has been operated since 1981 and is one of the biggest landfill sites in Podlasie Province of Poland, where more than 400000 m^3 of municipal waste is deposited annually. The leachate amount is about 25000 m^3 per year. The leachate samples were taken four times a year since March 2004 till September 2021 and analysed by accredited laboratory of Regional Inspectorate of Environmental Protection, as a part of landfill monitoring system. The following parameters were monitored: pH, Pb, Cu, Zn, Cr, Hg. All the parameters were measured according to the standard methods for the examination of water and wastewater (APHA, 2005).

After measuring the laboratory parameters, the Leachate Pollution Index (LPI) and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) Index were calculated.

Leachate Pollution Index

Leachate Pollution Index was developed by Kumar and Alappat (2005a) in order to assess the leachate pollutant potential of landfill sites. According to this method, the total leachate quality rating is represented by a single value calculated according to the equation (Kumar & Alappat, 2005a):

$$LPI = \frac{\sum_{i=1}^{m} w_i p_i}{\sum_{i=1}^{m} w_i}, \tag{1}$$

where:
LPI – is the weighted additive leachate pollution index,
wi – is the weight for the *ith* pollutant variable,
pi – is the sub-index score of the *ith* pollutant variable, and
m – is the number of leachate pollutant parameters for which data are available.

The LPI is calculated on the base of maximum 18 parameters and their weights (*wi)* based on significance levels given by the panelists. The values of *pi* for different leachate parameters are obtained from sub-index average curves developed for each parameter. The weights and averaged sub-index curves are illustrated and reported in the literature (Kumar & Alappat, 2005a).

When some of the leachate parameters are unknown, m < 18 and:

$$\sum_{i=1}^{m} w_i < 1 \tag{2}$$

According to the findings of Kumar and Alappat, equation (1) can be used with acceptable accuracy to calculate LPI values, even when data for some pollutants are unavailable (Kumar & Alappat, 2005a). A study conducted by Kumar and Alappat (2005a) and Mor et al. (2018) confirms that reliable assessments of leachate quality can be achieved based on a limited number of parameters. Due to the unavailability of data on all parameters required for LPI, the Leachate Pollution Index in this study has been calculated on the basis of seven parameters, whose testing is mandatory as part of the monitoring of municipal landfills in Europe. The analysed parameters include pH, Pb, Cu, Zn, Cr and Hg.

TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a popular multi-criteria decision-making technique. TOPSIS consists of ordering the analysed objects according to the closest distance to the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution was formed as a combination of the best points of each criterion and the negative ideal solution – the worst points of each criterion. The importance weights of the criterion were determined on the basis of the entropy method. TOPSIS method consists of several stages (Hwang & Yoon, 1981; Hajduk, 2021). Figure 1 and Table 1 present important stages and formulas of TOPSIS technique.

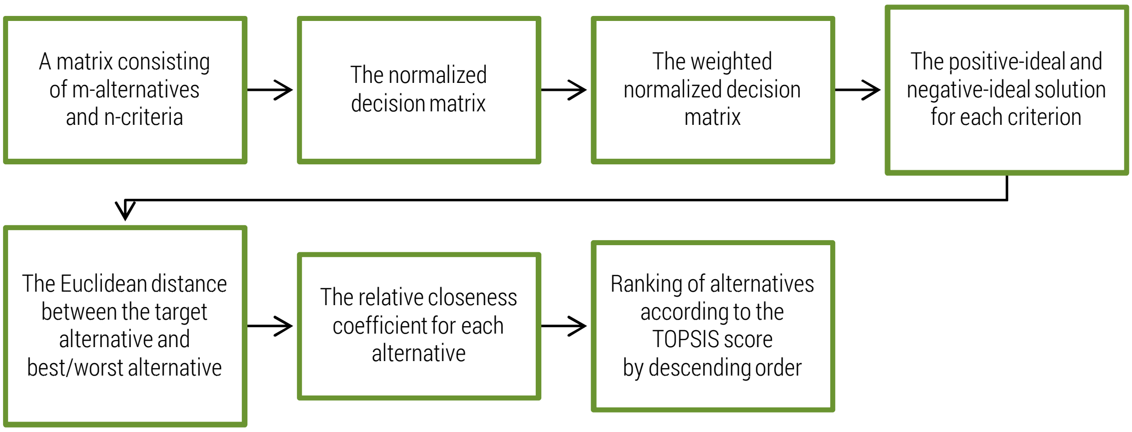

Figure 1. Stages of TOPSIS technique

Table 1. Stages and formulas of TOPSIS technique

Stages of TOPSIS technique	**Formulas**	
A matrix consisting of m-alternatives and n-criteria	$X = [x_{ij}] = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}$ where: x_{ij} represents the value of the j-th criterion $(j = 1, 2, \dots, n)$ for the i-th alternative (city, $i = 1, 2, \dots, m$) and $x_{ij} \epsilon$ R.	(3)
The normalized decision matrix	$R = [r_{ij}] = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}$ where: $r_{ij} = \begin{cases} \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} & \text{, when } j \epsilon \text{ stymulant} \\ 1 - \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} & \text{, when } j \epsilon \text{ destymulant} \end{cases}$	(4) (5) (6)

Stages of TOPSIS technique	Formulas	
The weighted normalized decision matrix	$V = [v_{ij}] = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix}$ where: v_{ij} means the weighted and normalized value of the j-th criterion ($j = 1, 2, \ldots, n$) for the i-th alternatives (cities, $i = 1, 2, \ldots, m$).	(7)
The positive-ideal and negative-ideal solution for each criterion	$A^+ = (v_1^+, v_2^+, \ldots, v_m^+)$ $A^- = (v_1^-, v_2^-, \ldots, v_m^-)$ where: $v_m^+ = \left\{\left(\max_i v_{ij} \mid j \in S\right), \left(\min_i v_{ij} \mid j \in D\right) \mid i = 1, 2, \ldots, n\right\}$ $v_m^- = \left\{\left(\min_i v_{ij} \mid j \in S\right), \left(\max_i v_{ij} \mid j \in D\right) \mid i = 1, 2, \ldots, n\right\}$ $S = \{j = 1, 2, \ldots, m \mid j\ represent\ the\ bigger - the\ better\ attribute\}$; $D = \{j = 1, 2, \ldots, m \mid j\ represent\ the\ smaller - the\ better\ attribute\}$.	(8) (9)
The Euclidean distance between the target alternative and best/worst alternative	$d_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2}$ $d_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2}$ where: d_i^+ – the positive ideal solution d_i^- – the negative ideal solution	(10) (11)
The relative closeness coefficient for each alternative	$RC_i = \frac{d_i^-}{d_i^+ + d_i^-}$ where: $0 \leq RC_i \leq 1, i = 1, 2, \ldots, m$.	(12)

Source: authors' work based on Sojda (2020).

Statistical analysis

For data analysis, a STATISTICA software was used in this study. The basic statistical analysis included calculation of minimum, maximum and mean (mediane for pH) value. Measures of variability were reported in standard deviation. In order to evaluate degree of association and admissibility of the TOPSIS method for leachates quality assessment, the correlation and factor analysis was performed.

Results of the research

Landfill leachate characteristic

The basic statistical characteristics of analysed leachate in 2004-2021 are given in Table 2.

The median pH of leachate was 8.30, with a minimal value of 5.7 (Sep 2001) and a maximum of 9.2 (Dec 2014). Leachate generated during the first 8 years of observation (2004-2012) was characterised by pH values in the range of 7.12-8.6 (Figure 2b). As landfill ages, the pH of leachates increased, and in the next 10 years (2012-2021), it ranged within the values of 7.8-9.2. The exception is the last observations, where pH of 5.7 was observed. The slightly alkaline nature of landfill leachate confirms the mature stage of the analysed landfill (Wdowczyk & Szymańska-Pulikowska, 2021).

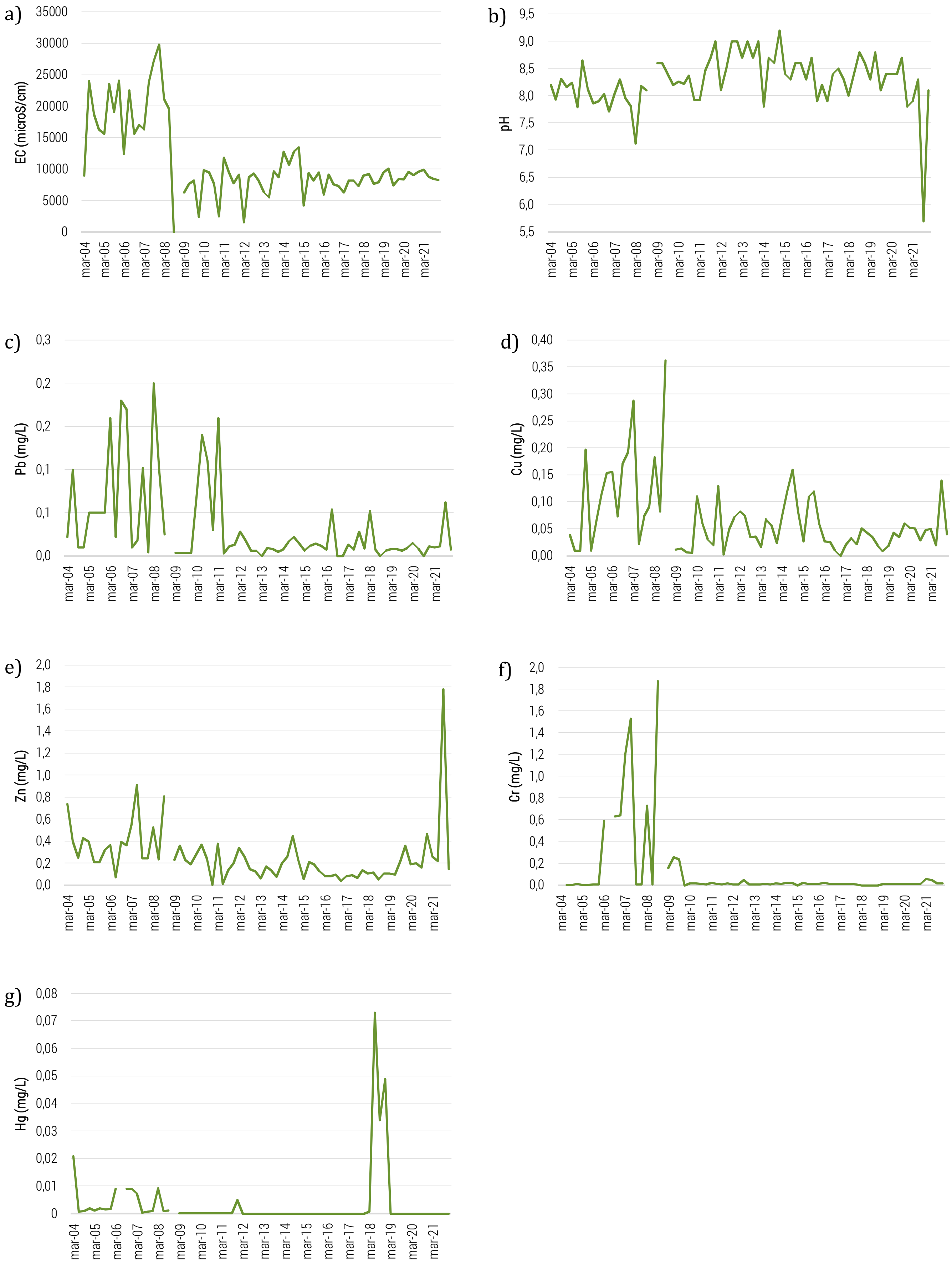

Figure 2. Value of EC (a), pH (b) and concentration of Pb (c), Cu (d), Zn (e), Cr (f) and Hg (g) in analysed leachate from the period 2004-2021

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Table 2. Basic statistical characteristic of analysed leachate

Parameter	Unit	Min	Max	Average	Stand dev	Standard limits*
EC	µS/cm	25.0	29800	11111	6077	-
pH	-	5.7	9.2	8.30**	-	6.5-9.0
Pb	mg/L	0	0.2	0.04	0.05	0.5
Cu	mg/L	0	0.36	0.07	0.07	0.5
Zn	mg/L	0.01	1.78	0.26	0.25	2.0
Cr	mg/L	0	1.87	0.14	0.35	0.1
Hg	mg/L	0	0.07	0.01	0.02	0.06

* Standard limits according to the regulation of MMEIN of 12.07.2019 (Act, 2019).
** value of mediane.

The average EC value of landfill leachate was 11 110 µS/cm and ranged from 25 µS/cm (Sep 2008) to 29 800 µS/cm (Dec 2007). In the first 8 years of observations (2004-2012), the value of EC was higher, after which it stabilised and, in the last five years of the study, remained at a range of 6 000 – 9 000 µS/cm (Figure 2a). The obtained values are within ranges observed in other landfills described in studies of Wdowczyk and Szymańska-Pulikowska (2021), Hussein et al. (2019), Kjeldsen et al. (2002), Naveen et al. (2017). Electroconductivity is not included in the LPI calculation, but this parameter gives general information about the quality of the analysed leachate.

The average value of heavy metals in analysed landfill leachate can be ordered as follows: Zn (0.26 mg/L)> Cr (0.14 mg/L) > Cu (0.07 mg/L)>Pb (0.04 mg/L)>Hg(0.01 mg/L). In the first years of observations, the concentrations of analysed heavy metals were higher, and this was the result of the lower pH value at this time (Figure 1c-g). Nevertheless, the average (or even maximum) values of Pb, Cu, Zn and Hg do not exceed the highest admissible values in accordance with regulation MMEIN of 12.07.2019. The exception is Cr, whose average value in the analysed period was above the admissible value of 0.1 mg/L. In the case of Pb, Cu, Zn and Hg, both sorption and precipitation are believed to be significant mechanisms for the immobilisation of these metals (Kjeldsen et al., 2002). In addition, the solubilities of many metals with sulfides, which are typical in landfills, are low because they are capable of forming precipitates with them. Cr is an exception to this because it doesn't form insoluble precipitates with sulfate, and that is why its concentration in analysed leachate is higher. According to Liu and Sang (2010), Cr is easier to dissolve in a neutral leaching medium, and this can be the reason for the elevated concentration of Cr in the analysed leachate.

LPI and TOPSIS values characteristic

Figures 3÷5 show the LPI and TOPSIS values obtained for the analysed landfill site during the period 2004-2021. The basic statistical characteristic of analysed indexes is presented in Table 3. The mean value of the LPI was 5.24 and ranged from 3.13 (Jun 2006) to 6.92 (Jun 2007). The range of the LPI value was 3.79. Both the low value of range and the standard deviation (Table 2) indicate a low variability of the quality of the analysed parameters. This also proves that the decomposition processes within the waste body are stable and that the pollution potential of the landfill leachate does not change over time.

According to Szymańska-Pulikowska (2010) and Munir et al. (2014), the LPI value at most landfills ranges between 4 and 18. The observed LPI from the analysed landfills was lower than that observed at large landfills with operation time longer than 10 years, indicating that the pollution load in leachate is not high. The highest LPI values were observed in the years 2007 (5.87), 2014 (5.63) and 2018 (5.83). The lowest values were recorded in 2017 (4.78) and 2016 (4.8) (Figure 5). The low LPI value suggests that the landfill leachate is stabilised, which is also indicated by the EC value and heavy metals concentrations given in Table 2 and Figure 2. Low LPI values also result from the low concentration of heavy metals in the leachate. As the landfill site ages, the concentration of heavy metals in the leachate decreases due to the alkalinisation of the reaction resulting from the consumption of organic acids by methane bacteria and due to the formation of insoluble forms of metals, primarily in the form of sulphides (Tałałaj, 2013). The low LPI values for long-exploited (matured) landfills have also been reported by Kumar and Alappat (2005a), Szymańska-Pulikowska (2010), Wdowczyk and Szymańska-Pulikowska (2021).

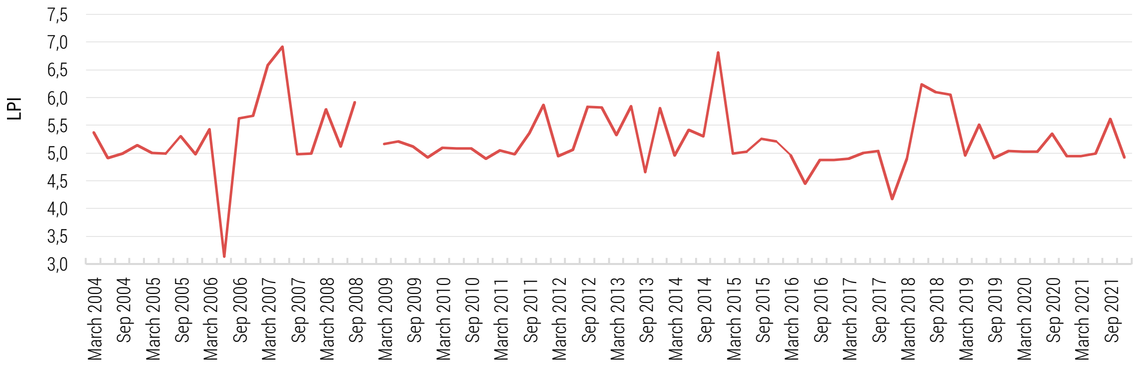

Figure 3. Value of LPI index in the analysed period 2004-2021

Table 3. Basic statistic characteristics for LPI and TOPSIS indexes

	Minimum	Maximum	Average	Standard deviation
LPI	3.13	6.92	5.24	0.554
TOPSIS	1	70	35.5	20.205

The average value of the TOPSIS index was 35.5 and ranged from 1 (Jun 2011) to 70 (Jun 2018) (Table 3, Figure 4). The reported range of 69 was greater than the LPI range. It suggests that TOPSIS may be an indicator that is more sensitive and more responsive to changes in leachate quality.

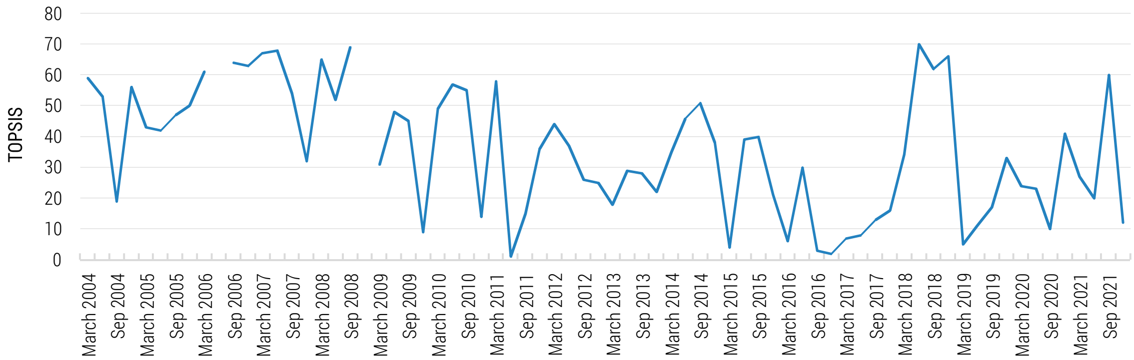

Figure 4. Value of TOPSIS index in the analysed period 2004-2021

The lowest values of the TOPSIS index were observed in 2016 and 2017 and were 10.3 and 11.0, respectively (Figure 5). The highest values were recorded in 2006 (62.7), 2007 (55.3), 2008 (62.0) and 2018 (58.0). The time of occurrence of the highest and lowest values of the TOPSIS index correlates with the time of occurrence of the highest and lowest LPI index values. This proves that the quality of the analysed leachates is well described and characterised by the TOPSIS index.

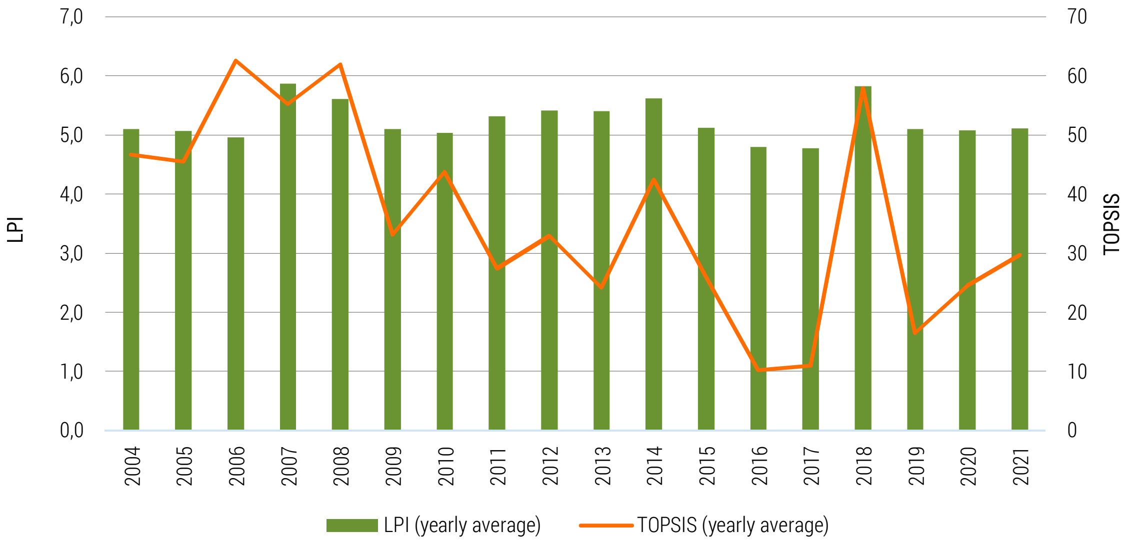

Figure 5. Yearly average values of LPI and TOPSIS indexes in the analysed period 2004-2021

LPI vs TOPSIS analysis

In order to assess the correlation of LPI and TOPSIS with leachate quality parameters and to evaluate the suitability of TOPSIS for assessing leachate quality, correlation analysis and principal factor analysis were performed. Their results are presented in Table 4 and Table 5.

Table 4. Result of correlation analysis

	pH	Pb	Cu	Zn	Cr	Hg	Sum of $\lvert r_i \rvert$ $\sum_{i=1}^{n}\lvert r_i\rvert$	Average$\lvert r_i \rvert$ $\frac{\sum_{i=1}^{n}\lvert r_i\rvert}{n}$
LPI	0.20	0.04	0.27	0.32	0.23	-0.22	1.28	0.21
TOPSIS	-0.27	-0.23	0.58	0.57	0.17	-0.58	2.40	0.40

The correlation coefficients for LPI value and analysed parameters were in the range $0.20 \leq |r| < 0.35$. Pb was the exception, with a correlation coefficient of 0.04. In the case of TOPSIS, the highest correlation coefficient $|r|$ was observed for Cu (0.58), Zn (0.57) and Hg (0.58). For the pH, Pb and Cr, the correlation coefficients were in the range $0.20 \leq |r| < 0.30$, which is similar to the LPI. Based on the results of the correlation analysis, the sum of the absolute values of the correlation coefficients was calculated, and then the average of the absolute values of the correlation coefficient was calculated using the formulas:

$$\overline{r_{LPI}} = \frac{\sum_{i=1}^{n}|r_i|}{n}, \tag{14}$$

$$\overline{r_{TOPSIS}} = \frac{\sum_{i=1}^{n}|r_i|}{n}, \tag{15}$$

where:
r_{LPI} and r_{topsis} – average from absolute values of the correlation coefficient,
n – number of analysed parameters,
r_i – correlation coefficient for *i-th* parameter.

The value obtained for LPI: 0.21 and TOPSIS: 0.40 indicates the average absolute value of the correlation of pollutant parameters with a given pollution index (LPI or TOPSIS). A higher *r*-value for TOPSIS indicates a good correlation of this index with the analysed pollutant parameters. It also explains why TOPSIS is an index that is more sensitive and more responsive to changes in leachate quality, as described in the analysis of LPI and TOPSIS index values.

Multivariate principal factor analysis was used to analyze structures in relationships between variables and to assess the usefulness of TOPSIS for assessing the leachate quality. Factor analysis is a statistical method used to describe variability among observed, correlated variables. Principal component analysis, with Varimax rotation, was selected as the factor extraction method. The selection of the number of significant factors was based on Cattell's 'scree plot'. The results of the factor analysis present three factors describing 67% of the variability in leachate quality (Table 5).

Table 5. Result of principal factor analysis

	Factor 2	Factor 1	Factor 3
pH	-0.06	0.93	0.02
Pb	-0.28	0.22	0.29
Cu	0.70	-0.28	-0.28
Zn	0.59	-0.49	-0.21
Cr	0.04	0.12	0.86
Hg	-0.52	0.30	-0.46
LPI	0.78	0.42	0.12
TOPSIS	0.82	-0.31	0.25
% Variance	0.30	0.21	0.16

Factor 1 explains 30% of the total variance and is marked by high loadings (| r |> 0.5) of Cu (| r | = 0.70), Zn (| r | = 0.59), Hg (| r | = 0.52), LPI (| r | = 0.78) and TOPSIS (| r | = 0.82). Based on the obtained data, we can conclude that the values of both LPI and TOPSIS were influenced mainly by Cu, Zn, and Hg and, to a lesser extent, by Pb Pb (| r | = 0.28). It is noteworthy that the factor loadings of LPI and TOPSIS were very high, exceeding the value of 0.75. We would thus conclude that both indicators explain well the variability of leachate quality resulting from the content of the analysed pollutants in leachate. Factor 2 covers 21% of the variability in leachate quality, and the highest factor loading is characterised by pH (| r | = 0.93). The absolute values of the factor loadings of the other pollutants do not exceed 0.3 and remain at a similar level within the range of 0.12 and 0.30. The third factor explains 16% of the variability in leachate quality and is marked by high loading of Cr (| r | = 0.86). This factor describes the conditions for the presence of chromium in leachates, which differ from the other metals analysed. Sorption and precipitation processes play an important role in the immobilisation of heavy metals, and the dominant mechanism for lowering the concentration of metals in leachate is their precipitation in the form of sulphides, which are formed under anaerobic conditions of the landfill environment. An exception to this rule is chromium, which does not form sulfides. Unlike other metals, its mobility increases with increasing pH, which was observed during leachate quality analyses (Kjeldsen et al., 2002). Additionally, Cr is not subject to precipitation as carbonates, and this may be another reason for the release of these metals. We can conclude that Factor 3 describes the conditions for the occurrence of Cr in leachate.

Conclusions

The literature review and analyses carried out in this paper showed that both methods, LPI and TOPSIS, can be used as an indicator of leachate pollution. The conducted studies indicated that the TOPSIS method is more sensitive and allows for detailed and accurate observation of changes in leachate quality. Like the LPI method, TOPSIS can support leachate quality assessment at municipal landfills. The additional advantage of this method is that TOPSIS can be used for any number of contaminant parameters without limitation on scope, quantity, and weight. Similar to the LPI, it can be used to compare the variability of leachate quality over time or to analyse differences in leachate quality from different landfill sites.

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The contribution of the authors

Conceptualization, I.A.T. and S.H.; methodology, I.A.T. and S.H.; validation, I.A.T. and S.H.; formal analysis, I.A.T.; investigation, I.A.T.; resources, I.A.T.; funding acquisition, I.A.T. and S.H.; data curation, I.A.T. and S.H.; supervision, I.A.T.; project administration, I.A.T.; writing – original draft, I.A.T.; writing – original draft (part 2.3. TOPSIS), S.H.; writing – review & editing, I.A.T. and S.H.

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OCENA JAKOŚCI ODCIEKÓW ZE SKŁADOWISKA ODPADÓW ZA POMOCĄ WSKAŹNIKA ZANIECZYSZCZENIA ODCIEKAMI (LPI) I TECHNIKI PREFERNENCJI KOLEJNOŚCI WEDŁUG PODOBIEŃSTWA DO IDEALNEGO ROZWIĄZANIA (TOPSIS)

STRESZCZENIE: Zmienność i zróżnicowanie jakości odcieków składowiskowych stanowi trudność zarówno w ocenie stopnia zagrożenia przez nie środowiska jak i w doborze odpowiedniej metody ich unieszkodliwiania lub oczyszczania. Dlatego ilościowe określenie potencjału zanieczyszczenia odciekami jest niezbędne w zarządzaniu składowiskami i może być wykorzystane do oceny prawidłowości eksploatacji składowiska oraz jego wpływu na otaczające obszary. Celem pracy była ocena skuteczności metody TOPSIS (Technique for Order preference by Similarity to an Ideal Solution) oraz jej przydatności w określaniu potencjału zanieczyszczenia odcieków w porównaniu do metody LPI (Leachate Pollution Index). Analizie poddano jakość odcieków pobieranych w latach 2004–2021 ze składowiska odpadów komunalnych. Do badań przyjęto 7 wskaźników fizyczno-chemicznych odcieków (pH, EC, Pb, Cu, Zn, Cr, Hg) i w oparciu o ich wielkości obliczono indeksy LPI i TOPSIS na przestrzeni 18 lat. Uzyskane wyniki wskazują, że metoda TOPSIS jest bardziej czuła i pozwala na szczegółową i dokładną obserwację zmian jakości odcieków. Może być stosowana dla dowolnej liczby wskaźników zanieczyszczeń bez ograniczeń co do zakresu, ilości i wagi tych wskaźników. Metodę TOPSIS można również wykorzystać do porównywania zmienności jakości odcieków w czasie lub do analizy różnic w jakości odcieków z różnych składowisk.

SŁOWA KLUCZOWE: składowisko, jakość odcieków, indeks zanieczyszczenia odcieków, TOPSIS

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