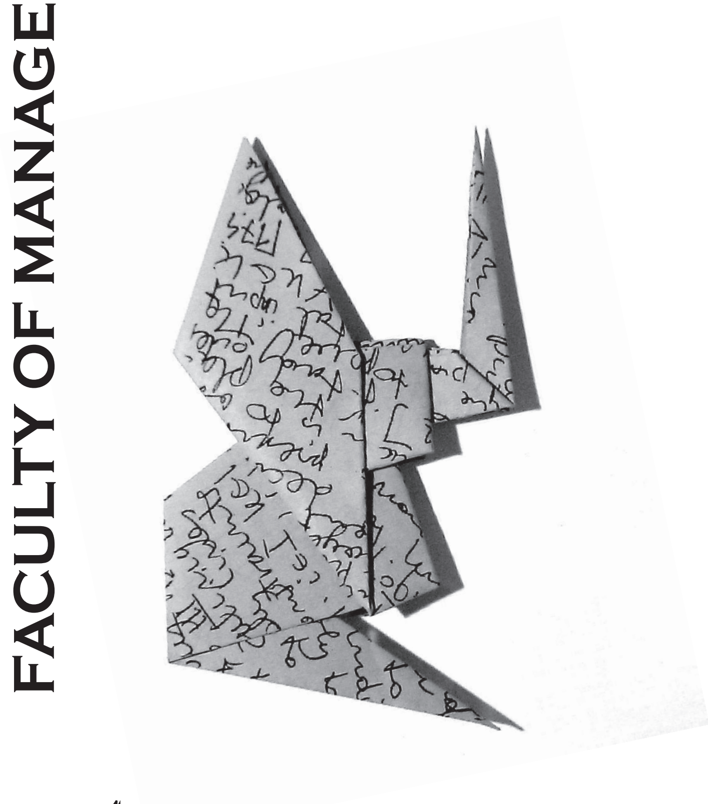
DECISION MAKING IN MANUFACTURING AND SERVICES

FACULTY OF MANAGEMENT



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Analysis of Six Sigma Tools Utilization in Phases of DMAIC Cycle

Bartosz Soliński*

Abstract. Six Sigma has been developed and successfully used in many organizations for many years. The use of Six Sigma in process-improvement requires the systematic and disciplined use of specific tools and techniques in the DMAIC cycle. The DMAIC cycle includes five phases: Define, Measure, Analyze, Improve, and Control; this is one of the most popular Six Sigma improvement cycles that are used in improving existing processes. When improving processes in accordance with the DMAIC cycle, it is important to have knowledge of the tools and techniques that are used and the ability to select them for the specifics of a project and the appropriate phases of the cycle. This article critically reviews the literature on the use of individual tools in the appropriate phases of the DMAIC cycle and uses a semi-structured interview method with specialists in the field of using Six Sigma. The obtained results of the analyses can contribute to the study of the validity of using individual tools and techniques for the effective use of Six Sigma and provide a useful comparative review for theoreticians and practitioners who want to use the appropriate tools in the DMAIC cycle.

Keywords: Six Sigma, DMAIC, tools application, project

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1. INTRODUCTION

The skills and knowledge that are related to creating high-quality products and services are currently the main element of building a competitive advantage. In order to meet these requirements, companies are implementing various concepts and methods of improvement; among these, Six Sigma plays a significant role.

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Six Sigma is a comprehensive and flexible system for achieving, maintaining, and maximizing business success (Pande et al., 2000); it is guided by a close understanding of customer needs, reliance on facts, the use of data and statistical analysis, and attention to the management and improvement of business processes. Six Sigma has its origins in the USA; it was created by Motorola in the 1980s. It was then significantly developed by General Electric (GE) and other companies (including Allied Signal), which began to successfully use it in their business strategies.

Six Sigma is considered to be one of the most important concepts that have been used in the quality-improvement process over the last two decades (Garza-Reyes, 2015). It has been adopted as a major continuous improvement initiative by many world-class manufacturing and service companies (Sreedharan et al., 2018) in order to increase competitive advantage, process efficiency, and productivity or to improve customer service (Anthony & Karaminas, 2016). When properly implemented, Six Sigma brings a number of benefits to a company; these are not only financial in nature but can also include the following: increased customer satisfaction, culture change, product/service development, increased productivity and process efficiency, cost reduction, and many other benefits that result from using the full potential of a company's infrastructure and human resources. The result is products and services that are made cheaper, better, and in a shorter amount of time.

Six Sigma is still being developed and successfully used in the largest organizations in the world. Alongside concepts such as lean management and the theory of constraints (ToC), it has become a global standard for process improvement.

In principle, Six Sigma has been defined in many ways – both in the literature on the subject and in the nomenclature that is used by the companies that adapt and use it in practice: a strategy, initiative, concept, program, method, technique, etc. It is a method for improving and striving for perfection with customers and making their requirements centrally embedded by creating the set of tools and techniques that are used in the structured DMAIC cycle (Define – Measure – Analyze – Improve – Control) (Soliński, 2019).

In order to achieve success, the use and implementation of Six Sigma requires the systematic and disciplined use of specific tools (Anthony et al., 2007). The significant impact of the tools and techniques that are used in Six Sigma was also pointed out by (Yang & El-Haik, 2003), who stated that "Six Sigma is a method that provides companies with tools to improve the efficiency of their business processes," and (Harry & Schroeder, 2000), who stated that "Six Sigma focuses on the aspect related to basing on facts (data) and using the appropriate set of tools in order to identify sources of errors and how to eliminate them."

It seems that the key to the success of Six Sigma lies in the rigorous use of the appropriate tools in the DMAIC cycle. Six Sigma is a comprehensive set of tools and techniques; it is, therefore, important to have appropriate knowledge of most of the tools and techniques as well as the ability to apply them correctly in the appropriate phases of the DMAIC cycle. Despite the numerous theoretical contributions, there is still a lack of comparative studies and limited empirical validations.

The conducted research was based on the methods of critical review of the subject literature on the use of the individual tools and techniques in the appropriate phases of the DMAIC cycle and the method of semi-structured interviews with specialists in the field of using Six Sigma. The obtained results of the analyses can be a contribution to the research on the validity of using individual tools for the effective use of Six Sigma and also constitute a useful comparative review for practitioners who want to use the appropriate tools and techniques in the DMAIC cycle.

2. DMAIC CYCLE IN SIX SIGMA

There is no single definition of Six Sigma; many authors have presented their own, very different, attempts to define it by looking at it from different perspectives. This is not surprising, because Six Sigma can take on various individualized forms in each organization, combining with the strategy and culture of a company or becoming one of many methods for solving problems. A relatively often-cited definition in the literature is the one that was proposed by Pande et al. (2000), which stated that "Six Sigma is a comprehensive and flexible system for achieving, maintaining and maximizing business success. It is guided by a close understanding of customer needs, based on facts, the use of data and statistical analysis, and paying attention to the management, improvement and discovery of business processes." This definition shows the fundamental principles that have led to the release of the potential of Six Sigma in every organization.

The use of Six Sigma requires the use of a structured and logical cycle of activities. The main and dominant cycle that is used in Six Sigma is the DMAIC cycle, which is used to solve problems and improve processes, products, and services. It was proposed by Motorola and GE in the 1980s. One can see some similarity between this cycle and the most popular improvement cycle (PDCA), which was proposed by Shewhart and Deming. DMAIC consists of five phases and was built in such a way that it can be used for more-complex problems and improvement projects in which there is a large amount of data. Each phase was designed to ensure the consistency of the implemented improvement projects with the business goals of the company and to focus on the factors that are key to customer satisfaction; it requires the involvement of one's employees as well as the allocation of time and resources for continuous improvement. The DMAIC cycle is used to improve existing processes; in order to design new processes and adapt them to customer requirements, the *Design for Six Sigma* approach is used, which distinguishes itself with IDOV and DMADV cycles, among others.

Table 1 presents a brief description of the individual Six Sigma DMAIC phases that have been proposed by the author.

Table 1. *Characteristics of DMAIC cycle phases*

Phase	Characteristics and purpose of each phase
Define	Identifying and clearly describing a problem, and defining the key customer requirements and goals to be achieved within a defined project scope.
Measure	Identifying and measuring the key process characteristics in order to define the current situation (baseline).
Analyze	Analyzing the data on the key process characteristics in order to identify any sources of variations as well as their root causes.

Table 1 cont.

Phase	Characteristics and purpose of each phase
Improve	Generating solutions that reduce variability and eliminate root causes, selecting them, implementing them, and assessing their impacts on the process.
Control	Standardizing the work methods, processes, and applied solutions, confirming and evaluating the achieved effects, and providing the mechanisms for monitoring and maintaining the effects over time.

3. TOOLS AND TECHNIQUES THAT ARE USED IN DMAIC CYCLE

An extremely important role in the success of Six Sigma projects is played by the use of the appropriate tools and techniques that have become key elements of Six Sigma's success. It is the use of the appropriate tools and techniques in appropriate manners that affects the effectiveness and efficiency of Six Sigma projects, which contributes to solving existing problems and achieving measurable business effects.

The size and complexity of the tools that are used can also become a problem, as was indicated by Firka (2010); he stated that the teaching and training that require a lot of time often go beyond the actual requirements for the use of the appropriate tools that are related to the specificity of the Six Sigma project. It is therefore important to focus on the most important Six Sigma tools.

The variety of tools often causes anxiety among team members and their leaders – especially if these are among the first initiatives of this type that are undertaken in companies. It seems that it would be useful to determine which tools are more frequently used by other practitioners or other companies with similar specifics. It can be risked to say that the most frequently used tools can be considered to be the most practical tools that can be easily understood and applied in Six Sigma projects.

Six Sigma Black and Green Belt training includes Six Sigma toolkits, which include the most commonly used tools and are often associated with the body of knowledge of global organizations such as ASQ (American Society for Quality). The participants of any training should be familiarized with these tools. Both theoreticians and practitioners should be interested in determining which tools are used in the appropriate phases of the DMAIC cycle. Hahn et al. (2000) also pointed out that, very often, the skills that are acquired during training in advanced tools (such as DOE, SPC, regression analysis, and variance analysis) are only temporary and that employees very often forget about them and do not use them in their Six Sigma projects.

By analyzing the literature on the subject regarding the most frequently and least frequently used tools, several authors have distinguished the following sets of tools that are used in Six Sigma:

- Antony and Banuelas (2002):
  - Most frequently used tools: cause-effect analysis, Pareto analysis, control charts, and run charts.
  - Least frequently used tools: DOE, QFD, FMEA, 5S, Poka-Yoke, and SPC.

- Curry and Kadasah (2002):
  - Most frequently used tools: checklists, process maps and brainstorming, sampling, and control charts.
- Bayazit (2003):
  - Most frequently used tools: Pareto analysis, SPC, cause-effect diagrams, and process maps.
- Antony et al. (2005):
  - Most frequently used tools: process maps, histogram, cause-effect analysis, run chart, SPC control charts, FMEA, process capability analysis, and Poka-Yoke.
  - Least frequently used tools: nonparametric tests (e.g., Mann–Whitney Test), affinity diagram, project charter, SIPOC, quality cost analysis, run charts, measurement system analysis (MSA), and QFD.
- Antony and Desai (2009):
  - The most commonly used (statistical) tools are histogram, control charts, and process capability analysis (SPC). The most commonly used problem-solving tools are brainstorming, cause-effect analysis, Pareto analysis, process mapping, and project charter.
  - The least frequently used tools (statistical) are nonparametric tests (Mann–Whitney test), Taguchi, and DOE methods. The least frequently used tools for solving problems are affinity diagrams, force-field analysis, and matrix analysis.
- Cauchick-Miguel et al. (2012):
  - The ten most commonly used tools by companies are data-collection sheet, histogram, Pareto analysis, brainstorming, control charts, process capability analysis (SPC), process map, and measurement system analysis.
  - The ten least commonly used tools are OCAP, PDPC, EVOP, operational testing, PERT/CPM, market testing, stakeholder analysis, FTA, and accelerated life-testing.

It should be noted that the studies that were presented above were conducted in different industries and countries, so the specifics of a given project may slightly distort the overall picture of the tools that are used. Another aspect that was argued by Linderman et al. (2006) was that, when project goals are very ambitious and difficult to achieve, increasing the use of more-advanced Six Sigma tools resulted in higher project performance. On the other hand, Antony et al. (2005) stated that easier-to-use tools are used more often and, therefore, attract more users as compared to more-sophisticated and -complex statistical tools. Hahn et al. (2000) stated that more-advanced tools become more important as organizations move to more-complex problems. From these statements, it can be concluded that the more-complex tools are, unfortunately, less frequently used in organizations, which may result in significantly smaller benefits for companies than they could be.

Given these findings, the need to know the tools and techniques that can be used in Six Sigma seems to be crucial for achieving better results in Six Sigma projects.

In order to systematize this knowledge, matrices have been published that show the individual tools in the DMAIC cycle. These tools are most often assigned to one or more phases of the DMAIC cycle.

One of the attempts to systematize this issue is the matrix that was presented by Hagemeyer et al. (2006), which showed the use of 34 tools in the individual phases of the DMAIC cycle. Similar matrices were also proposed by Cauchick-Miguel et al. (2012), in which 58 tools were shown in the individual phases. An important element of the guidelines for the use of the appropriate tools that are used with interest by Six Sigma project leaders are the lists that have been presented by large organizations that deal with quality, such as the previously mentioned ASQ or the popular guides from The Six Sigma Memory Jogger (Table 2).

Table 2. *DMAIC phase tools matrix*

Tool	D	M	A	I	C
Affinity diagram	×				
Brainstorming			×	×	
Capacity indices		×	×		×
Cause-and-effect analysis			×		
Charter (project charter)	×				
Commitment scale				×	
Communication plan	×				×
Control chart	×	×		×	×
CTQ tree	×				
Data-collection techniques	×	×			
Data types		×			
Designs of experiments			×		
Flow chart (process map)	×	×	×	×	
FMEA			×	×	
Focused-problem statement			×		
Gantt chart	×			×	
Histogram		×	×	×	
Hypothesis testing			×		
Interrelationship graph			×		
Involvement matrix				×	
Kano model	×				
MSA		×			
Operational definitions		×			

Table 2 cont.

Tool	D	M	A	I	C
Pareto diagram	×	×		×	
PDCA				×	×
Prioritization matrix				×	
Process-management chart					×
Six Sigma Level		×		×	
Scatter diagram			×		
SIPOC	×				
Six Sigma Storyboard					×
Taguchi loss function		×			
Tollgate review	×	×	×	×	×
Tree diagram			×		
$Y = f(x)$ formula	×	×	×		

Source: own study based on (Brassard et al., 2017)

4. OWN RESEARCH AND DISCUSSION OF RESULTS

The research was conducted on a purposefully selected group of experts by taking their knowledge and experience in the field of Six Sigma into account. The experts that took part in the research were people from the automotive and household appliances industries who had certified training in the field of Six Sigma Black Belt and had completed at least three improvement projects using the DMAIC cycle in the previous three years.

In order to show the use of the individual tools in the DMAIC cycle, a semi-structured interview was conducted with Six Sigma Black Belt experts on the subject of their implemented Six Sigma projects and the tools that they used in them. For this purpose, a set of questions and a survey questionnaire with answers were prepared in order to collect the research material. Based on a literature research and the author's experience, 115 specific tools and techniques were identified that could be used during the implementation of a Six Sigma project. The interview technique also allowed for the easy addition of a given tool if it was reported by any experts during the interviews. The interviews were conducted; then, the interview results were developed using the completed questionnaire, thus making a critical analysis of the experts' statements. This allowed for obtaining a set of tools that have been used in Six Sigma projects in the automotive and household appliances industries in the Polish economic reality (which are presented in Table 3).

In the analysis of the tools and techniques that were used, their names were standardized, and some tools were gathered into groups:

– graphical analysis – includes all kinds of presentation charts (pie, scatter, bar, etc.);

- descriptive statistics – include location measures (mean, mode, and median), dispersion measures (range, standard deviation, and variance) and shape measures (kurtosis and skewness);
- normality of distribution test – includes matching statistical distribution to empirical data, its analysis using nonparametric statistical tests (Shapiro-Wilk, Chi^2 and Anderson-Darling);
- control charts – contains cards for continuous features (X-R, X-S, and Xi–MR) and attributive features (p, np, c, and u).

Table 3. *Tools and techniques that have been used in DMAIC phases in automotive and household appliances industries*

D	M	A	I	C
Project charter Risk matrix Stakeholder analysis Pareto CTQ tree Process map SIPOC	Data-collection plan Data collection sheet Graphical analysis Descriptive statistics Six Sigma Level Measurement system analysis (MSA)	Brainstorming Ishikawa diagram 5 Whys Pareto Descriptive statistics Histogram Test of distribution normality Statistical hypothesis testing Correlation and regression analysis Process capability analysis Graphical analysis FMEA	Brainstorming Benchmarking Ranking method Process map Action plan Poka-Yoke	Standardized operating procedure One-point lesson Out-of-control-action plan Descriptive statistics Six Sigma level Histogram Test of distribution normality Statistical hypothesis testing Graphical analysis Process capability analysis SPC control charts

Based on the research, 31 tools and techniques that were used during the implementations of Six Sigma projects were identified. As already mentioned, some of the tools were aggregated into homogeneous groups. Taking each individual tool that was indicated in the study into account, the number of tools increased to 38. According to the experts, using the right tools and techniques in appropriate ways affects the effectiveness and efficiency of Six Sigma projects. Their effective use significantly contributes to solving existing problems and achieving measurable business effects. As can be seen in the list, selected tools and techniques can be used in several phases depending on a team's needs. The experts also drew attention to this aspect during their interviews. The research also indicated that the use of the appropriate tools and techniques depended on the specificity of a project and the specificity of an industry.

Then, the research results regarding the tools that were used in the DMAIC cycle (Table 3) were compared with the most frequently used tools lists that had been presented in various scientific publications (which were described earlier in the publication). From this group of the most frequently used tools in Six Sigma, all were among the tools that were given by the experts in the study that was conducted by the author.

The obtained results were also compared with the set of tools that were presented in one of the most popular Six Sigma books – The Six Sigma Memory Jogger II (Table 2). The tools and techniques that were indicated in the research constituted about 70% of all of the Six Sigma tools that were indicated there.

In the conducted study, the experts came from the automotive and household appliances industries. Expanding the sample with additional experts from other industries as well as using a random sample may contribute to increasing the representativeness of the results.

Taking this into account, it was possible to recommend additional tools for Six Sigma practitioners that were additionally based on the literature research and the author's own research (who is a certified Lean Six Sigma Master Black Belt). In the author's opinion, these would help in the effective and efficient implementation of Six Sigma projects. The set of tools that were presented in Table 3 (own research) should be supplemented with the following:

1. Project-management tools:
   - communication plan used to develop communication strategy with project stakeholders (Define phase);
   - Gantt chart – used to develop and manage project schedule (Define phase);
   - gate review – so-called review of Six Sigma project phases, performed after each DMAIC phase (all phases);
   - Impact-Effort Matrix – a decision-making tool for prioritizing and selecting the most appropriate solutions.
2. Statistical tools:
   - box plot – used to show distribution of studied feature (Measure, Analyze, and Control phases);
   - ANOVA and MANOVA – analysis of variance used to assess influences of studied factors (Analyze and Control phases).
3. Modeling tools:
   - DOE – design of experiments (Analyze and Improve phases).
4. Project-closure tool:
   - Six Sigma Storyboard – presents key analyses, decisions, and results that are obtained during DMAIC improvement cycle in simple graphical form (Control phase).

The final results (with supplemented tools and techniques in the Polish economic reality) are presented in Table 4.

Table 4. *Tools and techniques used in DMAIC phases*

D	M	**A**	**I**	**C**
Project charter Risk matrix Stakeholder analysis Communication plan Gantt chart Pareto CTQ tree Process map SIPOC	Data-collection plan Data collection sheet Graphical analysis Descriptive statistics Six Sigma level Measurement system analysis (MSA)	Brainstorming Ishikawa diagram 5 Whys Pareto Descriptive statistics Histogram Box plot Test of distribution normality Statistical hypothesis testing Correlation and regression analysis ANOVA and MANOVA Process-capability analysis Graphical analysis FMEA	Brainstorming Benchmarking Ranking method Impact-Effort matrix Process map Action plan Poka-Yoke DOE	Standardized operating procedure One-point lesson Out-of-control-action plan Descriptive statistics Six Sigma level Histogram Test of distribution normality Statistical hypothesis testing ANOVA and MANOVA Graphical analysis Process capability analysis SPC control charts Storyboard

5. CONCLUSIONS

Six Sigma is a comprehensive set of tools and techniques that can be used during the implementations of improvement projects. These are used in the appropriate DMAIC phases, which play extremely important roles in running Six Sigma projects and become key elements of its success. From this point of view, it is important for a team that implements a Six Sigma project to focus on the most important tools and techniques in order to effectively and efficiently implement it.

The conducted research allowed us to obtain a set of tools that have been used in Six Sigma projects in the automotive and household appliances industries in the Polish economic reality. It should be noted that the use of the appropriate tools and techniques depends on the specifics of a project and the specifics of an industry; therefore, factors such as industry type, organizational differences, project complexity, and the level of one's Six Sigma maturity may influence the selections of the tools and should be carefully considered. In this study, the tools and techniques were assigned to the individual phases of the DMAIC cycle. Based on the research, 31 tools and techniques were identified that were used in the individual phases of DMAIC. Additionally, the author suggested nine additional tools and techniques for use, which allowed for the identification of a total of 40 tools. The review of the literature on the subject allowed for the conclusion that the tools and techniques that were indicated in the study included a set of the most frequently used tools that had been presented in various scientific publications and overlapped by 70% with the tools that had been indicated in the popular Six Sigma tools books. From this point of view, it is important for a team that implements a Six Sigma project to focus on the most important tools and techniques in order to effectively and efficiently implement it.

Based on the presented research results, Six Sigma project leaders (Green and Black Belts) and their teams can refer to the information that was provided in Table 4 and apply the listed tools in the corresponding phases of the DMAIC cycle (bearing in mind that the industry in which they operate may determine the use of additional specialized tools).

REFERENCES

Antony J. & Banuelas R. (2002). Key ingredients for the effective implementation of Six Sigma program. *Measuring Business Excellence*, **6**(4), pp. 20–27. **DOI:** https:// doi.org/10.1108/13683040210451679.

Antony J. & Desai D.A. (2009). Assessing the status of Six Sigma implementation in the Indian industry: Results from an exploratory empirical study. *Management Research News*, **32**(5), pp. 413–423. **DOI:** https://doi.org/10.1108/01409170910952921.

Antony J. & Karaminas H. (2016). Critical assessment on the Six Sigma Black Belt roles, responsibilities, skills and training: A global empirical study. *International Journal of Quality and Reliability Management*, **33**(5), pp. 558–573. **DOI:** https://doi.org/10.1108/IJQRM-08-2014-0106.

Antony J., Kumar M. & Madu C.N. (2005). Six sigma in small- and medium-sized UK manufacturing enterprises: Some empirical observations. *International Journal of Quality & Reliability Management*, **22**(8), pp. 860–874. **DOI:** https://doi.org/10.1108/02656710510617265.

Antony J., Antony F.J., Kumar M. & Cho B.R. (2007). Six Sigma in service organizations: Benefits, challenges and difficulties, common myths, empirical observations and success factors. *International Journal of Quality & Reliability Management*, **24**(3), pp. 294–311. **DOI:** https://doi.org/10.1108/02656710710730889.

Bayazit O. (2003). Total quality management (TQM) practices in Turkish manufacturing organizations. *The TQM Magazine*, **15**(5), pp. 345–350. **DOI:** https://doi.org/10.1108/09544780310502435.

Brassard M., Finn L., Ginn D., Ritter D., (2017). *The Six SIGMA Memory Jogger II: A Pocketguide of Tools for Six Sigma Improvement Teams – Memory Jogger*. GOAL/QPC, Salem, NH

Cauchick-Miguel A., Satolo E., Marcos Andrietta J. & Araújo Calarge F. (2012). Benchmarking the use of tools and techniques in the six sigma programme based on a survey conducted in a developing country. *Benchmarking: An International Journal*, **19**(6), pp. 690–708. **DOI:** https://doi.org/10.1108/14635771211284279.

Curry A. & Kadasah N. (2002). Focusing on key elements of TQM – evaluation for sustainability. *The TQM Magazine*, **14**(4), pp. 207–216. **DOI:** https://doi.org/10.1108/09544780210429816.

Firka D. (2010). Six Sigma: an evolutionary analysis through case studies. *The TQM Journal*, **22**(4), pp. 423–434. **DOI:** https://doi.org/10.1108/17542731011053343.

Garza-Reyes J.A. (2015). Lean and green – A systematic review of the state of the art literature. *Journal of Cleaner Production*, 102, pp. 18–29. **DOI:** https://doi.org/10.1016/j.jclepro.2015.04.064.

Hagemeyer C., Gershenson J.K. & Johnson D.M. (2006). Classification and application of problem solving quality tools. A manufacturing case study. *The TQM Magazine*, **18**(5), 2006, pp. 455–483. **DOI:** https://doi.org/10.1108/09544780610685458.

Hahn G.J., Doganaksoy N. & Hoerl R. (2000). The evolution of six sigma. *Quality Engineering*, **12**(3), pp. 317–326. **DOI:** https://doi.org/10.1080/08982110008962595.

Harry, M. & Schroeder R. (2000). *Six Sigma: The Breakthrough Management Strategy Revolutionizing the World's Top Corporations*. New York: Doubleday.

Linderman K., Schroeder R.G. & Choo A.S. (2006). Six Sigma: The role of goals in improvement teams. *Journal of Operations Management*, **24**(6), pp. 779–790. **DOI:** https://doi.org/10.1016/j.jom.2005.08.005.

Pande P., Neuman R. & Cavanagh R. (2000). *The Six Sigma Way: How GE, Motorola, and other top companies are honing their performance*. New York, Chicago, San Francisco, Lisbon, London, Madrid, Mexico City, Milan, New Delhi, San Juan, Seoul, Singapore, Sydney, Toronto: McGraw-Hill.

Pyzdek T. (2000). *The Six Sigma Handbook*. New York, Chicago, San Francisco, Lisbon, London, Madrid, Mexico City, Milan, New Delhi, San Juan, Seoul, Singapore, Sydney, Toronto: McGraw-Hill Professional.

Soliński B. (2019). Innowacyjne koncepcje zarządzania jakością oparte o Lean management i Six Sigma – charakterystyka i porównanie. In: N. Iwaszczuk (red. nauk.), *Innowacyjność w działalności gospodarczej*. Kraków: Wydawnictwo IGSMiE PAN, pp. 163–173.

Sreedharan V.R., Gopikumar V., Nair S., Chakraborty A. & Antony J. (2018). Assessment of critical failure factors (CFFs) of Lean Six Sigma in the real-life scenario: Evidence from manufacturing and service industries. *Benchmarking: An International Journal*, **25**(8), 3320–3336. **DOI:** https://doi.org/10.1108/BIJ-10-2017-0281.

Yang K. & El-Haik B. (2003). *Design for Six Sigma: A Roadmap for Product Development*. New York, Chicago, San Francisco, Lisbon, London, Madrid, Mexico City, Milan, New Delhi, San Juan, Seoul, Singapore, Sydney, Toronto: McGraw-Hill. **URL:** https://leaninstitute.sk/wp-content/uploads/2021/02/01Kniha_Kai-Yangg-Basem-El-Haik_Design-for-6Sigma-A-roadmap-for-Product-development-EN.pdf [5.10.2021].

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Deadhead Minimization Problem in Multi-Depot Public Transport System

Robert Szczyrbak*

Abstract. This paper addresses a vehicle scheduling problem in the public transport system of Krakow, Poland. The primary objective is to develop and evaluate a mathematical model for assigning bus schedules to depots in a way that minimizes non-revenue (deadhead) kilometers. The proposed model, referred to as the Deadhead Minimization Problem in Multi-Depot Public Transport System (DMPMDPTS), seeks to reduce the total distance that is traveled by vehicles from their home depots to the starting points of their first scheduled routes and from the final terminals back to their depots. The model assumes fixed-route structures and known deadhead distances between terminals. Real-world data that was based on the Krakow Municipal Transport (KKM) was used to validate and verify the model. The optimization model was implemented in AMPL and solved using the GLPK Integer Optimizer (v4.43). Computational experiments were conducted across multiple cases that differed in their constraints and parameters in order to assess the model's flexibility and performance. In all of the cases, optimal solutions were obtained in brief computation times. Compared to the existing operational schedules, the model consistently reduced deadhead kilometers. Case 1 achieved improvements without altering the numbers of vehicles per depot, while Case 2 led to further reductions of the costs of redistributing vehicles among depots, resulting in a less-balanced load structure. These findings demonstrated the model's potential for supporting decision-making in depot allocation within public transport operations.

Keywords: Vehicle Scheduling Problem, public transport system, crew rostering, deadhead minimization, deadhead kilometers, optimization, Operations Research

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1. INTRODUCTION

The primary goal of any enterprise is to maximize its profit through efficient operations. A prevailing trend in modern management is minimizing costs – particularly those that are associated with resource consumption. Lean Management principles advocate for companies to focus on what the customer truly values and to eliminate any components that do not add value to their product or service; any such non-value-adding elements represent a loss for the company. Modern Lean Management systems should be closely integrated with rational resource-management practices. It is essential for companies to assess whether changes in one area will lead to unintended consequences in others. Mathematical models and algorithms serve as valuable tools in this regard, allowing businesses to simulate changes and their potential impacts across different spheres (e.g., Agnetis et al., 2019; Gdowska et al., 2018; Korcyl et al., 2016; Książek et al., 2021; Villarreal et al., 2016). These tools' versatility allows for the calculations of possible costs or gains that would result from any proposed changes, making them essential in optimizing various aspects of operations. Moreover, mathematical models can be effectively applied in the designs of new systems or areas of operation (Csalódi et al., 2021).

In the context of a communications company (such as one that provides public transportation services), the price structure of the service – including fuel costs, vehicle depreciations, and employee salaries – becomes a key factor (Szczyrbak, 2016). A unit of measurement called "vehicle kilometers traveled" (VKT) is used to assess transportation efficiency and optimize operations. Companies typically develop operational plans based on policies that are aligned with contracts from public transport organizers. These plans detail the required numbers of vehicles and employees as well as their work schedules (Szczyrbak & Gdowska, 2017).

The research that is presented in this paper focuses on the scheduling of the bus brigades that serve daytime lines within the Krakow Municipal Transport (KKM) system; specifically, the study narrows its scope to the brigades of a single carrier that operates within the city's central transportation area. The objective of this research was to develop the Deadhead Minimization Problem in Multi-Depot Public Transport System (DMPMDPTS) and employ mixed-integer linear programming to solve it.

This paper is structured as follows. In Section 2, the research gap of insufficient research on deadhead kilometer minimization using exact methods is identified based on a systematic literature review. In Section 3, the Deadhead Minimization Problem in Multi-Depot Public Transport System (DMPMDPTS) is introduced together with the dedicated MILP model; then, the results are presented for three cases. The main conclusions are presented in Section 4.

2. PAPER POSITIONING

Planning in public transportation encompasses several broad areas – each involving decisions regarding the designs and operations of specific service components (Gdowska, 2018). From the passenger's perspective, the system should meet their needs by providing affordable and efficient public transportation. Additional criteria may include comfort, route selection, and the frequency and number of transfers that are required to reach their destination (e.g., work, school). From the transportation company's point of view, the system must also generate as much profit as possible. The primary challenge in its planning lies in finding a balance that satisfies both the passengers' and the company's needs. The complexity of transportation planning necessitates decisions at strategic, tactical, and operational levels. The communication system that is described in this paper distinguishes between the planning responsibilities of the organizer and the carrier (Borndörfer et al., 2017). The organizer is the entity that is responsible for managing the public transportation, while the carrier is the operator that is contracted to execute specific routes as per agreements with the organizer.

The relationship between objective service–performance indicators and passenger satisfaction in public transport is multifaceted. While measurable aspects such as punctuality, frequency, and travel time are important, they do not always align directly with perceived quality. Achieving high levels of user satisfaction requires a balanced approach that considers both operational efficiency and the subjective expectations of travelers (Friman & Fellesson, 2009). Mathematical optimization models for train timetabling can significantly reduce passenger waiting times at public transit terminals. By optimizing arrival and departure schedules, these models contribute to more-efficient service operations and improved passenger experience through better synchronization and reduced transfer delays (Hassannayebi et al., 2017).

The organizer's role encompasses strategic and tactical decision-making in public transport. Their responsibilities include determining how the network will operate and contracting carriers to run the selected routes. The key planning areas for the organizer include route and service planning, service-frequency planning, and timetable planning. Route and service planning involves creating a sequence of stops that a particular line will serve as well as determining the required type of fleet for each route. Service-frequency planning refers to deciding how many trips will be made on a given route at various times of the day (with the flexibility to adjust based on demand). Timetable planning involves scheduling the actual times of the departures and arrivals for each route, thus ensuring efficient service and meeting passenger needs. Intelligent bus routing relies on analyses of heterogeneous human mobility patterns to enhance route planning and service delivery. Integrating diverse data sources such as travel demands, temporal flow variations, and location-based behaviors enables more-adaptive and -efficient transit systems that better respond to passenger needs and urban dynamics (Iliopoulou & Kepaptsoglou, 2019).

Frequency planning (which is a critical part of service scheduling) is determined by the demand for the trips on a route at various times of the day. The operator has the flexibility to adjust the number of trips based on time-of-day demand. Once the frequency is set, the organizer can use this data to make further strategic decisions, such as adjusting the overall route structure or adding additional services. A time-dependent passenger demand-driven timetable synchronization and optimization model can effectively minimize total travel time in urban subway networks. By adjusting scheduling parameters in response to dynamic passenger flows (such as those that can be observed in large systems like the Beijing subway), such models enhance operational efficiency and improve the overall passenger experience (Shang et al., 2018).

3. DEADHEAD MINIMIZATION PROBLEM IN MULTI-DEPOT PUBLIC TRANSPORT SYSTEM

Within the Krakow agglomeration, public transport services (i.e., the Krakow Municipal Transport) encompass both day and night bus lines. These services are operated by two main carriers: Miejskie Przedsiębiorstwo Komunikacyjne S.A. (MPK Kraków), and Mobilis sp. z o.o. Given the operational complexities and the potential for a single vehicle to serve both day and night routes, this study focuses exclusively on the day brigades that are managed by MPK Kraków. By "brigade," we understand a set of courses that a vehicle must navigate during one day; this set can includes several lines of a network, which is usually divided into two shifts. MPK Kraków deploys its bus fleet from three primary depots: Bieńczyce (PB), Płaszów (PP), and Wola Duchacka (PW). Each depot houses a specific assortment of bus models that reflect strategic allocations based on their operational requirements. For instance, the Bieńczyce depot primarily accommodates buses that are equipped with MAN and DAF engines, the Płaszów depot has historically housed Scania buses, and the Wola Duchacka depot includes vehicles that feature Mercedes-Benz engines (including gas-powered and electric buses). An estimated distribution of buses by type across these depots is presented in Table 1; this provides a foundational understanding of the resources allocated for day brigade operations within the MPK Kraków system.

Table 1. *MPK Kraków fleet (number of buses)*

	PB	PP	PW
Mini	18	0	29
Midi	0	0	13
Electric	0	0	6
Maxi	103	99	80
Mega	42	46	95

The primary criterion for the classification of the fleet is the lengths of the buses. Additionally, a distinct group of electric buses has been identified. The majority of the fleet consists of Maxi-class vehicles, which are characterized by a length of approximately 12 meters. Table 1 presents the distributions of the different bus types across all of the studied depots; of particular note is the deployment of the Mega-class buses – more than half of these are allocated to the Wola Duchacka depot. The data also indicates that the Płaszów depot operates only two classes of vehicles; this limited diversity may suggest an intentional specialization strategy that is aimed at operational efficiency and simplified maintenance. Tables 2 and 3 detail the allocations of the bus brigades to each depot as categorized by vehicle class and their utilization. An analysis of the data showed that the carrier did not fully utilize all of its resources, as at least one vehicle of each type remained unassigned at each depot. This approach likely served as a buffer against unexpected events such as mechanical failures or other disruptions (Szczyrbak, 2018).

Table 2. *Number of brigades of each type at given depot*

	PB	PP	PW
Mini	14	0	17
Midi	0	0	12
Electric	0	0	4
Maxi	89	76	52
Mega	31	35	77

Table 3. *Use of bus fleet*

	Baseline [%]		
	PB	PP	PW
Mini	78	n/d	59
Midi	n/d	n/d	92
Electric	n/d	n/d	67
Standard	86	77	65
Mega	74	76	81

The distributions of the brigades by vehicle class varied among the studied depots. The Bieńczyce depot handled just over 40% of the Maxi-class brigades, whereas Wola Duchacka managed the smallest number of brigades of this type. In contrast, the majority of the Mega-class brigades were concentrated at the Wola Duchacka depot. Overall, this depot was responsible for the highest number of brigades, while the Płaszów depot accounted for just over one-quarter of the total brigade assignments. Maxi-class vehicles were used to operate the majority of the brigades across the network – particularly those that served high-demand agglomeration routes. At the Bieńczyce and Płaszów depots, most of the brigades were assigned to Maxi-class buses. In both cases, the ratio of the Maxi-class brigades to those that were operated by the other bus types was approximately two-to-one. In contrast, the Wola Duchacka depot utilized a more diverse vehicle portfolio, with the brigades being distributed across five bus classes; nearly half of these were Mega-class brigades, while Maxi-class vehicles were allocated to roughly one-third of the total. To support the analytical component of this study, it was necessary to develop a distance matrix; the values that were used for this were generated using the Google Maps tool.

Two matrices were created for the purposes of analysis: one representing the distances between each depot and the respective starting stop, and another indicating the distances from the final stop back to the home depot (Szczyrbak, 2018).

3.1. Mixed-integer model for the DMPMDPTS

The brigade-allocation problem describes the brigade to the specific type of vehicle that is located at one of the depots. In the DMPMDPTS, the optimization criterion is to minimize the sum of the kilometers that the vehicles must travel to reach the post-arrival stop and to return after the end of the work. The problem assumes that inter-arrival trips are fixed in the schedule. For the DMPMDPTS, a MIP program (1)–(5) was developed. The notation that is used in the DMPMDPTS is presented in Table 4.

Table 4. *Notation*

Sets
Z – depots
T – types of vehicles
B – brigades
B^k – brigades that are served by vehicles of type k; $k \in T$, $B^k \subset B$
Parameters
a_{kp} – number of brigades of type k assignable to depot p
d_{jp} – total deadhead distance in kilometers for brigade j from depot p (comprised of trip from depot to first service stop and return from final stop to depot)
Decision variables
x_{jpk} – binary variable $x_{jpk} = 1$ if brigade j is operated by vehicle of type k from depot p; otherwise $x_{jpk} = 0$

The use of the binary variable assignment in the model was associated with the assignment of only one vehicle to a brigade. Compared to the model with an integer variable, the number of variables was much larger.

$$\min z = \sum_{j \in B} \sum_{k \in T} \sum_{p \in Z} d_{jp} x_{jpk} \tag{1}$$

$$\sum_{j \in B} x_{jpk} \le a_{kp}, \ k \in T, p \in Z \tag{2}$$

$$\sum_{p \in Z} x_{jpk} = 1, \ j \in B^k, \ k \in T \tag{3}$$

$$x_{jpk} \in \{0, 1\}, \qquad j \in B, \ p \in Z, \ k \in T \tag{4}$$

The optimization criterion in the objective function (1) aimed to minimize the total distance that was traveled by the brigades. Formulated as an inequality, Constraint (2) ensured that the number of brigades of a given type from a single depot did not exceed the limit that was specified by parameter a_{kp}. Constraint (3) ensured that each brigade was assigned exactly one vehicle of a specified type regardless of the depot to which it was assigned. By splitting the set of brigades by vehicle type, the constraints were simplified, thus reducing the need for separate constraints for each decision variable that specified the vehicle type. While this approach was manageable for the small size of the task, it may not scale well in larger instances. Constraint (4) enforced the binary nature of the decision variable.

To exclude a depot from operation, Constraint (5) could be introduced into the model; in the case that was considered in this study, the Płaszów depot (PP) was excluded from use.

$$x_{jpk} = 0, \qquad j \in B,\ k \in T,\ p \in Z,\ p \in \{PP\} \tag{5}$$

3.2. Computational experiments

The DMPMDPTS model was implemented in AMPL and solved using the GLPK Integer Optimizer, (Version 4.43). The computational experiments were conducted on a Lenovo G50 laptop that was equipped with an Intel Core i7 2.4 GHz processor and 8 GB of RAM. The model was used to analyze three distinct cases. Parameter a_{kp} is presented in Table 2, while parameter d_{jp} was provided by MPK Kraków and is included in the documentation of the research to which this paper refers (Szczyrbak, 2018). Across all of the cases, the value of parameter d_{jp} remained constant, whereas parameter a_{kp} varied depending on the scenario. This variability enabled the flexible assignments of all of the brigades of a given type to a single depot.

In Case 1, the allocations of the brigades were based on actual operational data that was obtained from MPK Kraków; parameter a_{kp} reflected these input values directly. The model results were compared against the real-world vehicle allocation. The number of decision variables in this scenario was 6105, with a memory usage of 4.7 MB. The model identified an optimal solution, and any key statistics that were related to the problem size and computational time were recorded. In Case 2, a new vehicle-to-brigade assignment was generated. Unlike the first scenario, the model allowed each depot to accept the maximum number of vehicles of each type. Although the assignment logic differed, the number of decision variables remained at 6105, while the memory usage increased to 6.2 MB. An optimal solution was again obtained. Case 3 followed the structure of Case 2 but introduced an additional constraint: the closure of one depot. This led to the reallocations of vehicles to those brigades that were under the new operational limitation. As in the previous scenarios, the number of decision variables remained unchanged (6105), while memory usage rose slightly (to 6.5 MB). The model successfully produced an optimal solution under this additional constraint.

Across all three cases, the DMPMDPTS model consistently identified optimal solutions. Based on the actual baseline data, the total distance that was traveled by the buses between their depots and their assigned routes – calculated as both departures from and returns to the depots – amounted to 6727 kilometers. In Case 1, this value was reduced to 6406.4 kilometers (representing a 4.76% decrease). This improvement was achieved under the constraint that no depot could accommodate more brigades than in the original allocation. In Case 2 (where the brigade-to-depot assignments were redesigned from scratch), the total distance dropped further – to 5820.9 kilometers (marking a 13.46% reduction as compared to the baseline). These favorable results motivated the development of Case 3, which explored the case of closing the Płaszów depot; however, this configuration led to a rise in the total distance to 5968 kilometers, which indicated that a depot's liquidation could negatively affect operational efficiency. A detailed comparison of the brigade assignments across the three variants is presented in Table 5.

Table 5. *Number of brigades assigned to depots after optimization*

	Baseline			Case 1			Case 2			Case 3		
	PB	PP	PW	PB	PP	PW	PB	PP	PW	PB	PP	PW
Mini	14	0	17	14	0	17	17	1	13	17	0	14
Midi	0	0	12	0	0	12	0	0	12	0	0	12
Electric	0	0	4	0	0	4	4	0	0	4	0	0
Maxi	89	76	52	89	76	52	67	26	124	75	0	142
Mega	31	35	77	31	35	77	56	1	86	56	0	87
Sum of brigades	134	111	162	134	111	162	144	28	235	152	0	255

The optimizations in Cases 2 and 3 led to significant changes in the allocations of the brigades across the three depots. In Case 2, the Płaszów depot was reduced to serving only 28 brigades, while Wola Duchacka depot took on 73 additional brigades as compared to the baseline. A notable shift in vehicle allocation occurred, with the Maxi vehicles serving substantial portions of the brigades. Furthermore, the Bieńczyce depot assumed responsibility for the operations of brigades with electric vehicles and saw an increase in the number of Mega-type vehicles. In Case 3 (with the closure of the Płaszów depot), the brigades that were previously assigned to Płaszów were redistributed to the other two depots. The Wola Duchacka depot then served 20 more brigades, while the Bieńczyce depot took on the remaining 8 brigades. Consequently, the Wola Duchacka depot was responsible for almost 60% of all of the brigades, while Płaszów depot handled only 7% of them. The changes in the depot allocations also influenced the distributions of the vehicles by class. In Case 2, a significant shift occurred in the Mini-class vehicles, with the Bieńczyce depot handling more than half of these brigades; this marked a noticeable deviation from the original data. The Maxi-class brigades were predominantly assigned to the Wola Duchacka depot (which experienced a considerable increase in its share), while the Płaszów depot saw a dramatic reduction in its role (now servicing only one brigade – a mere 1% of the total). The Mega-class brigades were distributed between the Wola Duchacka and Bieńczyce depots, with the Płaszów depot servicing only one brigade.

The brigade structure in the Bieńczyce depot became nearly balanced, with 46% of the brigades being served by Maxi vehicles and 39% by Mega vehicles. Notably, Case 2 also saw the electric bus brigades being allocated to the Bieńczyce depot – further contributing to the shift in depot responsibilities. The reduction in the role of the Płaszów depot was clearly illustrated by the graphical representation of the brigade share structures. As Case 2 progressed, a more balanced distribution emerged, with the Bieńczyce and Wola Duchacka depots increasingly absorbing the workload that was previously managed by Płaszów.

Table 6. *Summary of planned numbers of vehicles*

	Baseline			Case 1			Case 2			Case 3		
	PB	PP	PW	PB	PP	PW	PB	PP	PW	PB	PP	PW
Mini	18	0	29	18	0	29	22	2	23	22	0	25
Midi	0	0	13	0	0	13	0	0	13	0	0	13
Electric	0	0	6	0	0	6	6	0	0	6	0	0
Maxi	103	99	80	103	99	80	78	34	170	90	0	192
Mega	42	46	95	42	46	95	75	2	106	75	0	108
Total	163	145	223	163	145	223	181	38	312	193	0	338

In each of the developed variants that were analyzed, a lower total mileage was achieved as compared to the baseline case. In Case 1, the solution did not differ from the current state in terms of the number of vehicles that were used (see Table 6); the difference lay in the daily mileage (which was reduced by 320.6 kilometers). Assuming a cost of 6.6 PLN per truck kilometer, this translated into a daily savings of nearly 2000 PLN for the company. Case 2 introduced changes in the vehicle distribution; the newly developed allocation required the relocations of vehicles among the depots, which may have necessitated the expansions of one or more of the depots' facilities. The resulting savings amount to approximately 5500 kilometers per day. Additionally, Case 2 provided insights into the utilization levels of the individual depots, indicating that the Wola Duchacka depot experienced the highest load, with the lowest load being recorded at the Płaszów depot (whose closure was proposed in Case 3).

4. CONCLUSIONS

This study addresses the optimization of bus brigade utilization within public transportation by focusing on minimizing non-revenue-generating trips (commonly referred to as "deadhead kilometers"). A mathematical model was developed to achieve this objective; its effectiveness was evaluated using real-world data from the Krakow public transport system. The model demonstrated the capability of finding optimal solutions swiftly – even for complex cases – and it consistently outperformed the existing operational data in terms of reducing the total number of deadhead kilometers.

The findings aligned with previous research in the field. For instance, Mahadikar et al. (2015) developed a mixed-integer programming model to minimize dead kilometers in Bangalore's public transport by considering depot capacities and operational constraints. Similarly, Nasibov et al. (2013) applied various mathematical models to Izmir's bus system, achieving up to a 31.4% reduction in dead mileage under certain cases. These studies underscored the practical benefits of mathematical optimization in public transport operations

In the current study, case variants of the Deadhead Minimization Problem in Multi-Depot Public Transport System (DMPMDPTS) were tested. The key findings were as follows: (1) achieving a reduction in deadhead kilometers without altering the existing distribution of rolling stock among depots (Case 1); and (2) the additional minimization of deadhead kilometers by allowing the reassignments of vehicles between depots (Case 2). This indicated that strategic redistributions can lead to significant efficiency gains. These results demonstrated the DMPMDPTS's potential as a decision-support tool for those public transport authorities that are aiming to enhance their operational efficiency and reduce their unnecessary mileage.

REFERENCES

Agnetis A., Bianciardi C. & Iasparra N. (2019). Integrating lean thinking and mathematical optimization: A case study in appointment scheduling of hematological treatments. *Operations Research Perspectives*, **6**, 100110. **DOI:** https://doi.org/10.1016/j.orp.2019.100110.

Borndörfer R., Hoppmann H. & Karbstein M. (2017). Passenger routing for periodic timetable optimization. *Public Transport*, **9**, pp. 115–135. **DOI:** https://doi.org/10.1007/s12469-016-0132-0.

Csalódi R., Süle Z., Jaskó S., Holczinger T. & Abonyi J. (2021). Industry 4.0-driven development of optimization algorithms: A systematic overview. *Complexity*, **1**, 6621235. **DOI:** https://doi.org/10.1155/2021/6621235.

Friman M. & Fellesson M. (2009). Service supply and customer satisfaction in public transportation: The quality paradox. *Journal of Public Transportation*, **12**(4), pp. 57–69. **DOI:** https://doi.org/10.5038/2375-0901.12.4.4.

Gdowska K. (2018). How to assess balancing public transportation. In: *14th International Conference on Industrial Logistics, ICIL 2018 - Conference Proceedings*, Ben-Gurion University of the Negev, Beer-Sheva, pp. 79–86. **URL:** https://in.bgu.ac.il/en/engn/iem/ICIL2018/Pages/ICIL%20conference%20proceedings%20book%202018.pdf [10.10.2021].

Gdowska K., Viana A. & Pedroso J.P. (2018). Stochastic last-mile delivery with crowdshipping. *Transportation Research Procedia*, **30,** pp. 90–100. **DOI:** https://doi.org/10.1016/j.trpro.2018.09.011.

Hassannayebi E., Zegordi S.H., Yaghini M. & Amin-Naseri M.R. (2017). Timetable optimization models and methods for minimizing passenger waiting time at public transit terminals. *Transportation Planning and Technology*, **40**(3), pp. 278–304. **DOI:** https://doi.org/10.1080/03081060.2017.1283156.

Iliopoulou C. & Kepaptsoglou, K. (2019). Combining ITS and optimization in public transportation planning: state of the art and future research paths. *European Transport Research Review*, **11**, 27. **DOI:** https://doi.org/10.1186/s12544-019-0365-5.

Korcyl A., Ksiazek R. & Gdowska K. (2016). A milp model for route optimization problem in a municipal multi-landfill waste collection system. In: *13th International Conference on Industrial Logistics, ICIL 2016 - Conference Proceedings*, AGH University of Science and Technology, Krakow, pp. 109–118. **URL:** http://www.icil.zarz.agh.edu.pl/images/ICIL2016/ICIL2016_conference_proceedings_final.pdf [10.10.2021].

Książek R., Gdowska K. & Korcyl A. (2021). Recyclables collection route balancing problem with heterogeneous fleet. *Energies*, **14**(21), 7406. **DOI:** https://doi.org/10.3390/en14217406.

Mahadikar J., Mulangi R.H. & Sitharam T.G. (2015). Optimization of bus allocation to depots by minimizing dead kilometers. *Journal of Advanced Transportation*, **49**(8), 901–912. **DOI:** https://doi.org/10.1002/atr.1312.

Nasibov E., Eliiyi U., Ertaç M.Ö. & Kuvvetli Ü. (2013). Deadhead trip minimization in city bus transportation: A real life application. *Promet-Traffic & Transportation*, **25**(2), pp. 137–145. **DOI:** https://doi.org/10.7307/ptt.v25i2.1289.

Shang P., Li R., Liu Z., Xian K. & Guo J. (2018). Timetable synchronization and optimization considering time-dependent passenger demand in an urban subway network. *Transportation Research Record*, **2672**(8), pp. 243–254. **DOI:** https://doi.org/10.1177/0361198118772958.

Szczyrbak R. (2016). *Organizacja pracy brygad autobusowych obsługujących wybrane linie w Gminie Skawina* [Bachelor's Thesis]. AGH University of Science and Technology, Kraków.

Szczyrbak R. (2018). *Problem planowania brygad w sieci komunikacji aglomeracyjnej z wieloma zajezdniami na przykładzie Krakowskiej Komunikacji Miejskiej* [Master's Thesis]. AGH University of Science and Technology, Kraków.

Szczyrbak R. & Gdowska K. (2017). Tworzenie brygad autobusowych jako problem harmonogramowania zadań. *Logistyka*, **6**, pp. 58–60. **URL:** https://www.logistyka.net.pl/bank-wiedzy/item/91069-tworzenie-brygad-autobusowych-jako-problem-harmonogramowania-zadan [10.10.2021].

Villarreal B., Garza-Reyes J.A. & Kumar V. (2016). A lean thinking and simulation-based approach for the improvement of routing operations. *Industrial Management & Data Systems*, **116**(5), pp. 903–925. **DOI:** https://doi.org/10.1108/IMDS-09-2015-0385.

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Adoption of Electromobility in Urban Transport in Poland – Cost-Benefit Trade-Offs and Decision-Making Challenges

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Abstract. Electromobility is increasingly recognized as a cornerstone of sustainable urban transport strategies. This paper presents an analysis of selected economic, environmental, and infrastructural implications of transitioning from internal combustion engine vehicles to electric vehicles (EVs) in urban settings. Through a cost-benefit analysis, the study compares the purchase and operating costs of EVs and conventional cars across mini, compact, and premium market segments, accounting for factors such as energy consumption, fuel and electricity prices, annual mileage, and carbon emissions. The development and expansion of charging infrastructure, along with the integration of smart grid solutions and energy storage capabilities, are examined in the context of meeting the growing demand from a rising fleet of EVs. Additionally, the paper analyzes changes in urban mobility behaviors, highlighting the shift toward shared mobility and ecomobility, and discusses how these trends can reshape urban transportation to improve quality of life and reduce environmental impacts. Drawing on current trends, national electromobility development plans in Poland, and international best practices, the study identifies challenges and enablers for policymakers and decision-makers in the transportation and energy sectors, highlighting the need for coordinated planning and policy support to ensure the long-term viability and sustainability of electromobility in urban environments.

Keywords: electromobility, urban transport, electric vehicles, cost-benefit analysis, sustainable mobility, charging infrastructure, energy systems, infrastructure planning, environmental impact, transport policy, strategic management

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1. INTRODUCTION

Transport is a crucial pillar of economic competitiveness, social development, and global integration. It not only delivers high mobility, efficiency, comfort, and safety but also provides robust logistical support across supply, production, and distribution networks. However, transport systems generate significant external costs – including traffic accidents, congestion, fossil fuel dependence, air and noise pollution, extensive land consumption, and contributions to climate change – that have attracted growing scrutiny from researchers and policymakers in today's globalized landscape.

Since the 1990s, the surge in private car usage across European cities has introduced complex challenges that cut across environmental, climate, energy, and spatial planning policies. Urban mobility and infrastructure have thus emerged as central issues in the development of sustainable transport strategies, as the effects of motorization reverberate economically, socially, and ecologically. At the same time, the automotive industry has come under increasingly strict regulations, especially concerning safety and environmental impact. Consequently, addressing urban congestion and pollution requires innovative mobility concepts that are firmly aligned with the Sustainable Development Goals. Recent shifts in the vehicle market – fueled by the rising popularity of electric vehicles (EVs), evolving legislative frameworks, and targeted environmental initiatives – are accelerating the transition toward electromobility. This transformation is poised to reshape urban development and the energy sector by necessitating new infrastructure and distribution networks, while also opening up opportunities for enhanced energy storage. Furthermore, the anticipated increase in electricity demand is expected to drive improvements in the efficiency, reliability, and cost-effectiveness of energy production and supply (Wiśniowski, 2018).

This study examines how the rise of EVs is transforming urban mobility, with a particular focus on assessing the impacts of electromobility and the evolving travel behaviors in Poland. The paper is organized as follows: the first section discusses the current state of the electromobility sector in Poland; the second assesses the development of charging infrastructure; the third presents a cost comparison between electric and combustion vehicles based on empirical data; the fourth section analyzes emerging trends in urban mobility within the context of this paradigm shift; concluding remarks are presented in the final section.

2. THE ELECTROMOBILITY SECTOR IN POLAND

The electrification of transportation in Poland reflects not only technological and policy trends, but also a series of interdependent decisions made by various stakeholders. For policymakers, the challenge lies in balancing industrial development goals with environmental sustainability. For firms, it is a matter of cost competitiveness and regulatory compliance. For consumers, it depends on affordability, infrastructure availability, and perceived value (Sipiński & Bolesta, 2017).

Modern transport must address its negative environmental and climatic impacts – challenges that are especially evident in road transport's heavy reliance on petroleum-based fuels (Chłopek, 2002; Wasiak et al., 2014). Reducing emissions, lowering energy consumption, and increasing energy efficiency are now global priorities outlined in international frameworks, such as the 2015 Paris Agreement (United Nations Climate Change, 2015). In this context, the development of electromobility is central to many environmental, climate, and energy programs. Transitioning to electric vehicles (EVs) requires both continued technological innovation and heightened public awareness of their benefits. As electric drivetrains gradually replace traditional internal combustion engines, the automotive landscape is poised for significant transformation, opening opportunities for new market entrants who can first target niche segments before expanding more broadly (Flasza, 2017). Currently, electromobility is one of the fastest-growing sectors, with approximately 500,000 EVs sold globally each year and projections indicating that by 2040, nearly 40 million electric vehicles will be on the road – meaning one in every four cars could be electric (Krawiec & Krawiec, 2017).

The electrification of road transport is a key economic priority for the Polish government. In 2017, the publication of two strategic documents to support electromobility was followed by the 2018 Act on Electromobility and Alternative Fuels (*Ustawa z dnia 11 stycznia 2018 r. o elektromobilności i paliwach alternatywnych*, 2018). These initiatives aim to mitigate the environmental impact of Poland's transport sector – a major contributor to air pollution and related health concerns. Electric vehicles offer a promising emissions advantage, as their overall CO_2 output (when accounting for both energy production and consumption) is generally lower than that of combustion vehicles. Although Poland's current energy mix remains heavily reliant on coal, gradual shifts toward renewable energy and cleaner technologies are expected to reduce emissions further. Moreover, integrating EVs with renewable energy sources could further reduce emissions, potentially approaching near-zero levels (Denis & Kuczyński, 2017; Kucharska & Ruszel, 2016). The Act on Electromobility and Alternative Fuels also introduced mandatory shares of electric vehicles in the fleets of local government units. This requirement creates a direct compliance obligation for municipalities, influencing their procurement decisions and positioning them as essential actors in shaping the diffusion of electromobility (*Ustawa z dnia 11 stycznia 2018 r. o elektromobilności i paliwach alternatywnych*, 2018).

Placing Poland's electromobility development in a regional perspective helps identify transferable solutions and contextualize national challenges. Poland's situation can be better understood by comparing it with neighboring countries that share a similar fossil-dominated energy mix. In the Czech Republic and Hungary, coal and natural gas still dominate power generation, limiting the immediate emissions benefits of EV adoption. At the same time, both countries are pursuing gradual RES expansion and have introduced incentive schemes for EV uptake, including subsidies and preferential registration fees (European Alternative Fuels Observatory, 2020). Such regional parallels underline that Poland's challenges are not unique and that solutions – such as regional grid integration and harmonized infrastructure standards – may be scalable within Central and Eastern Europe.

Poland's efforts in this field are guided by the "Plan for Electromobility Development," which outlines goals such as improving air quality, enhancing energy security, and promoting technological and industrial growth. This plan is structured in three phases (Flasza & Matuszczyk, 2018):

1) 2016–2018– Pilot programs aimed at raising public awareness and stimulating interest in EVs;
2) 2019–2020 – Infrastructure development, notably the installation of charging stations and the initiation of short-run vehicle production;
3) 2020–2025 – Transition to mass production, integration with the national energy grid, and expansion of the public EV fleet (including government vehicles).

Despite these forward-thinking initiatives, challenges remain. Securing adequate funding for infrastructure, addressing public skepticism about EV benefits, expanding the underdeveloped charging network, and reducing high vehicle costs are significant issues. Additional barriers include limited vehicle range, longer charging times, and prevailing perceptions that EVs are costly or unproven. Nevertheless, driven by industrial readiness and technological improvements, the adoption of EVs is expected to surge between 2021 and 2024.

Beyond improving environmental outcomes, the growth of electromobility represents a new economic branch that can boost electricity demand, reduce reliance on oil imports, and stimulate Polish industrial development while creating jobs. An increasing number of EVs will necessitate expanded charging infrastructure, broader distribution networks, and innovative energy storage solutions. The Ministry of Energy estimates that the additional electricity demand could range from 2.3 TWh to 4.3 TWh by 2025 – a demand that may be met through both new power plant initiatives and more efficient use of existing capacities (Sipiński & Bolesta, 2017). For environmental and energy security reasons, a significant portion of this extra capacity must come from renewable sources.

The expansion of electromobility also intensifies the demand for lithium, a key ingredient in advanced batteries. By 2020, the electric vehicle manufacturing industry was already responsible for at least half of the global lithium demand. With the production of 10 million EVs offering ranges of up to 500 km, annual requirements had climbed to 110,000–150,000 tons. As EV adoption increases, reduced oil consumption is expected to enhance Poland's energy independence. While Poland is self-sufficient in electricity production, approximately 97% of its oil is imported – placing a strain on the trade balance and exposing the economy to volatile oil prices, which in turn can reduce disposable income.

The widespread adoption of EVs in Poland could significantly improve urban quality of life by reducing harmful emissions and noise. Given that transportation is a significant source of air pollution, especially in cities, the shift to electromobility promises substantial public health benefits by reducing healthcare costs and mitigating environmental damage. However, for these benefits to materialize fully, a significant portion of the energy used to power EVs must be generated from renewable sources.

A significant obstacle to achieving these goals is the underdeveloped charging infrastructure. The scarcity of charging stations, paired with the relatively high cost of electric vehicles and limited state support, poses a significant barrier to broader EV adoption. Addressing these challenges will require comprehensive legal reforms, increased investments, and targeted financial incentives. In this context, Norway's successful approach – characterized by high consumer awareness, penalties on combustion-engine vehicles, robust financial incentives, and an extensive charging network – serves as a helpful model. For Poland to meet its ambitious electromobility goals, these elements must be implemented in tandem, as neglecting any one of them could undermine the overall strategy. By examining these facets, this section highlights both the immense opportunity presented by electromobility and the critical challenges that must be addressed to secure a sustainable future for urban transport in Poland.

3. CURRENT STATUS AND PROSPECTS FOR THE DEVELOPMENT OF ELECTRIC CAR CHARGING INFRASTRUCTURE

Charging infrastructure development is both a technical and strategic decision-making issue. Overinvestment risks financial inefficiency, while underinvestment risks deterring adoption. Governments must therefore decide on phased roll-out strategies, while municipalities consider optimal geographical placement, and firms evaluate opportunities for private-public partnerships.

In many advanced economies, a comprehensive electric vehicle charging network is already in place, highlighting that the full realization of EV technology hinges on an adequately developed charging infrastructure. In the early stages of EV market growth, it is essential to align charging facility expansion with rising user demand. An imbalance – whether from an overabundance of EVs without sufficient charging stations or vice versa – could either discourage prospective users or lead to economically unsustainable operations. According to the "Electromobility Development Plan for Poland" issued by the Ministry of Energy, primary emphasis is placed on developing charging infrastructure in major urban conglomerates and along trans-European transport corridors traversing Poland. This plan focuses on establishing numerous publicly accessible EV charging points to accommodate the anticipated growth in electric vehicle usage. Global trends, corroborated by statistical analyses of EV market growth and European Union air quality regulations, indicate that Poland is entering the era of automotive electrification. With most charging expected to occur during off-peak nighttime hours, the national energy system is well-positioned to absorb the additional load, making EVs a flexible and beneficial component of the electrical grid.

According to the Polish Alternative Fuels Association (Polskie Stowarzyszenie Nowej Mobilności, 2021), at the end of November 2021, there were 1,784 publicly accessible charging stations in Poland, providing a total of 3,541 charging points. Of these, 1,102 were AC stations with 2,106 connectors, and 682 were DC fast-charging stations with 1,435 connectors. It is therefore necessary to distinguish between charging stations, understood as physical locations, and charging points, which refer to individual connectors available for use. The infrastructure remains concentrated in major urban centers such as Warsaw, Kraków, Katowice, Gdańsk, and Poznań, but expansion into medium-sized cities has also accelerated in recent years. While early deployments often provided free access, most operators now apply differentiated tariffs based on the charger's power rating and speed. National policy documents still anticipate substantial growth, with targets of several thousand additional charging points, accompanied by the development of centralized registration and monitoring systems to ensure interoperability and data exchange.

The plan further envisions that by 2025, the power grid will be upgraded to sufficiently support energy supplies for one million electric vehicles, with these EVs integrated as active regulatory elements of the system. However, two primary challenges have emerged in this developmental phase. The first concerns the optimal spatial and temporal distribution of charging stations. Overconcentration in a single area may overburden the local grid and prevent simultaneous full-power charging, while infrastructure limitations in certain regions may preclude installing additional units. The second challenge involves accommodating the growing electricity demand driven by an increasing EV population. Fast-charging facilities, for example, require high-capacity grid connections, despite their relatively low overall energy consumption. It is estimated that servicing one million EVs could nearly double the grid's maximum connection capacity, even as total annual electricity consumption rises by only about 1.5–3%. This disparity suggests that EV users should ultimately not only share the cost of the electricity they consume (per kilowatt-hour, kWh) and its distribution, but also contribute to the costs of grid connection and charging-station construction.

While the development of EV charging infrastructure is undoubtedly complex and capital-intensive, a phased, well-coordinated approach offers a sustainable path forward. Spreading the investment over time ensures that planning, preparation, and implementation are conducted in a manner that preserves energy system security and maintains manageable operating costs throughout the network.

Beyond the number and distribution of charging stations, the integration of EVs into the energy system also raises questions of grid stability and flexibility. A growing EV fleet will inevitably interact with the stability and security of Poland's electricity system. Increased charging demand may exacerbate peak load pressures, especially in urban centers where charging clusters are concentrated. At the same time, integrating EVs offers opportunities to enhance system flexibility. Vehicle-to-grid (V2G) technology, which enables bidirectional power flows, has been successfully tested in several European pilot projects as a tool to balance variable renewable energy sources and provide ancillary services (International Energy Agency, 2020). For decision-makers, the strategic challenge lies in aligning EV deployment with power system modernization and ensuring that charging infrastructure evolves alongside grid capacity and digital control mechanisms.

4. COST-EFFECTIVENESS ANALYSIS OF THE PURCHASE AND OPERATION OF AN ELECTRIC VEHICLE

The comparison of ICE and EV costs highlights both financial trade-offs and strategic decision points. Consumers evaluate affordability and long-term savings. Fleet managers assess the total cost of ownership and maintenance risks. Governments weigh fiscal incentives against budget constraints. This section provides structured evidence for these decision contexts, showing where EVs are already competitive and where barriers remain.

Electric vehicles have rapidly gained traction within the automotive industry. Today, most leading global manufacturers offer at least one electric-powered model, with many more in development. Although EVs have not yet emerged as full-scale competitors to internal combustion engine (ICE) vehicles worldwide, their rapid technological progress suggests that they will soon redefine market dynamics. Environmental concerns drive much of the growing interest in EVs. Urban areas, characterized by high traffic density and limited pollutant dispersion, often result in exceedances of air quality standards for particulate matter and nitrogen oxides, making them particularly vulnerable to the harmful effects of motor vehicle emissions. The shift to electric propulsion is seen as a promising strategy not only to mitigate these emissions but also to reduce dependence on dwindling non-renewable resources, such as crude oil. By eliminating tailpipe emissions and curbing reliance on petroleum-based fuels, EVs present a viable solution to these challenges. Today's automotive market is diverse, offering ICE, pure electric, and hybrid options. Each alternative has its unique advantages and drawbacks. EVs are noted for their low environmental emissions, lower operating costs on short trips, and a simpler mechanical design that reduces maintenance needs. In contrast, ICE vehicles incur higher fuel expenditures, emit significant pollutants, and generate more noise.

In Poland, the shift toward electromobility is an inevitable development for the domestic automotive industry. Although the initial purchase price of an EV is typically higher than that of a conventional vehicle, the reduced operating costs over time are frequently emphasized as a key benefit. To assess the overall cost-effectiveness, this analysis adopts three criteria: purchase costs, operating costs, and CO_2 emissions. Using these criteria, the profitability of owning and operating ICE vehicles versus EVs is evaluated across three market segments – mini, compact, and premium. The comparison is based on specific assumptions summarized in Table 1: vehicle purchase price (catalog prices); fuel consumption for ICE vehicles (4.2–9.5 l/100 km), electricity consumption for EVs (13–18 kWh/100 km), annual mileage of 30,000 km, fuel price (5.10 PLN/l), electricity price (0.55 PLN/kWh), and CO_2 emission factor for electricity production (614 g/kWh). The comparison of environmental impacts in this study was limited to CO_2 emissions due to data availability and the need for a standardized metric across vehicle categories. Nevertheless, it should be noted that particulate matter (PM) and nitrogen oxides (NO_x) frequently exceed permitted levels in Polish cities (Wasiak et al., 2014), and thus remain critical considerations for decision-makers in urban transport policy. The electricity price of 0.55 PLN/kWh reflects the assumption of home charging at household tariffs. In practice, using public charging infrastructure would entail higher costs, potentially eroding EVs' financial advantage in specific usage scenarios (Sipiński & Bolesta, 2017).

The selection of the Tesla Model S and Audi A8 as representatives of the premium segment warrants clarification. Although the Tesla is closer in market positioning to models such as the Audi A6, BMW 5 Series, or Mercedes E-Class, it was included here due to its comparable performance parameters and to reflect the growing role of

EVs in the upper market tier (Flasza, 2017). This choice does not imply full equivalence in prestige or pricing.

Table 1. *Technical parameters: fuel and electricity consumption, annual distance, fuel and electricity prices*

Vehicle model	Purchase price [PLN]	Fuel consumption [l/100 km]	Electricity consumption [kWh/100 km]
Mini Cooper	82,100	4.2	–
Nissan Note	67,800	6.1	–
Audi A8	429,000	9.5	–
BMW i3	162,100	–	13
Nissan Leaf	133,000	–	15
Tesla S	440,000	–	18

The first criterion – vehicle purchase price – reveals a significant disparity between EVs and ICE vehicles, particularly in the mini and compact segments, where EVs can be roughly twice as expensive as their combustion-engine counterparts. In the premium segment, however, price differences are minimal, suggesting a more competitive stance for EVs. The second criterion addresses operating costs. Estimates for covering 30,000 km annually, based on manufacturer data and standard assumptions, are summarized in Table 2. EVs have substantially lower operating costs than ICE vehicles. This cost efficiency primarily results from the simpler, more efficient construction of electric motors, which entail fewer components subject to wear or failure. Operating cost calculations exclude insurance and service costs, which vary widely depending on provider, vehicle segment, and user profile. Their omission reflects data limitations, but the relative differences in energy and fuel expenditures remain the dominant factors shaping cost-effectiveness (Wiśniowski, 2018).

Table 2. *Annual costs of fuel and electricity consumption for 30,000 km*

Vehicle model	Annual fuel cost [PLN]	Annual electricity cost [PLN]
Mini Cooper	6,426	–
Nissan Note	9,333	–
Audi A8	14,535	–
BMW i3	–	2,145
Nissan Leaf	–	2,475
Tesla S	–	2,970

Another vital operating cost driver for EVs is battery degradation and, in some cases, eventual replacement. Capacity fade is accelerated by temperature extremes, with both laboratory and review studies showing faster aging at elevated temperatures and performance loss in cold operation (Edge et al., 2021; Jaguemont et al., 2016). Field evidence from Scandinavia indicates that winter conditions materially reduce usable range: Norwegian Automobile Federation (NAF) and Motor magazine winter tests in 2020–2021 reported average shortfalls versus WLTP range in cold weather, with individual models showing reductions on the order of ~20–30% depending on conditions (Motor/NAF, 2021; NAF, 2020). In climates with marked seasonal swings – such as Poland – these thermal effects can both reduce effective driving range in winter and accelerate long-term capacity loss if thermal management is inadequate. Consequently, lifecycle evaluations should explicitly account for the risk of battery performance degradation and potential refurbishment/replacement costs.

Table 3. *Battery replacement costs for selected EV models*

Vehicle model	Estimated battery cost [PLN]	Battery capacity [kWh]
BMW i3	18,000	22
Nissan Leaf	25,000	30
Tesla S	40,000	55

Source: own elaboration based on secondary data from industry reports, service provider estimates, and press releases (not direct manufacturer list prices)

Original Equipment Manufacturers do not officially publish the exact costs of battery replacements. The estimates in Table 3 are compiled from secondary sources, including reports by Bloomberg New Energy Finance (2017), the International Energy Agency (2017), Frankel and Wagner (2017), and scientific analysis by Flasza (2017). Values were standardized to Polish zlotys [PLN] using the average exchange rates for 2017–2018.

The third evaluation criterion involves CO_2 emissions. Although EVs are often labeled 'zero-emission,' this holds only if the electricity used for charging is entirely renewable. In Poland, the renewable share in electricity production was already markedly higher than 10%: analyses for 2020 show coal's share fell below 70% and renewables increased, reflecting a significant – although still in the minority – contribution of RES to the power mix (Forum Energii, 2021). System statistics published for 2018–2020 likewise document the evolving fuel structure of production (Polskie Sieci Elektroenergetyczne, 2021). Given that fossil sources continued to dominate through 2020, indirect CO_2 emissions from EV charging remain non-negligible. Tables 4 and 5 present comparative emissions profiles for the selected ICE and EV models under these conditions. While the analysis is based on a single operational year, extending the horizon to a standard vehicle lifecycle (8–10 years) would provide a fuller picture of cost-effectiveness. Over extended periods, the lower operating costs of EVs tend to outweigh their higher purchase prices, reinforcing their attractiveness to decision-makers (Wiśniowski, 2018).

Table 4. *CO_2 emissions for selected ICE vehicles*

Vehicle model	Fuel consumption [l/100 km]	CO_2 emissions [kg/100 km]
Mini Cooper	4.2	11.8
Nissan Note	6.1	17.7
Audi A8	9.5	26.6

Source: own elaboration based on manufacturer fuel consumption data and standard CO_2 emission factors for gasoline (≈2.31 kg CO_2 per liter) (European Environment Agency, 2019)

Table 5. *CO_2 emissions for selected EV models (based on Poland's energy mix)*

Vehicle model	Electricity consumption [kWh/100 km]	CO_2 emissions [kg/100 km]
BMW i3	13	9.36
Nissan Leaf	15	10.80
Tesla S	18	12.96

Source: own elaboration based on electricity consumption data and the national grid emission factor (0.72 kg CO_2/kWh) reported by Polskie Sieci Elektroenergetyczne (2021)

Thus, although EVs emit less CO_2 per 100 km compared to ICE vehicles, they are not entirely emission-free under Poland's current energy conditions. Unlocking the full environmental potential of electromobility will require a broader shift toward renewable energy sources for electricity generation. Overall, the analysis – grounded in purchase costs, operating expenses, and CO_2 emissions – offers a nuanced view of the economic and environmental trade-offs between ICE vehicles and EVs across the mini, compact, and premium segments. In the mini and compact markets, the considerably higher purchase prices of EVs make them less cost-effective at present, despite their lower operating costs. Conversely, in the premium segment, where purchase price differences are minimal, EVs' lower operating costs may make them cost-effective as early as the first year of ownership. While this analysis focuses on CO_2 emissions as a measurable and comparable indicator, it is essential to note that other pollutants – particularly particulate matter (PM) and nitrogen oxides (NO_x) – are also critical in urban transport contexts. Exceedances of PM and NO_x limits have been repeatedly documented in Polish cities; however, due to data gaps and methodological limitations, these were not included in the quantitative assessment. Nonetheless, they remain essential factors for decision-makers concerned with public health.

Looking further ahead, while the current calculations do not yield a definitive verdict on which vehicle type is universally more cost-effective, they do illuminate the circumstances where EVs offer clear advantages – and where improvements, such as an increased share of renewable energy in the national grid, could further enhance their appeal. This analysis lays a critical foundation for evaluating future shifts in market dynamics as technology and energy infrastructure evolve.

5. ANALYSIS OF URBAN MOBILITY CHANGES IN THE CONTEXT OF ELECTROMOBILITY DEVELOPMENT

Electromobility not only affects vehicles – it reshapes urban mobility behaviors. For decision-makers in municipalities, this creates opportunities and challenges in planning integrated mobility solutions. For consumers, it shifts preferences toward shared and ecological mobility models. For firms, it drives innovation in business models such as car-sharing, leasing, and fleet electrification.

Over the past two decades, Poland's urban landscape has undergone significant transformation, driven by the expansion of urban structures and evolving transportation behaviors (Gdowska, 2018). These changes have culminated in increased overall mobility, reflecting shifts in both lifestyles and travel patterns. Mobility itself is a multifaceted concept. In transportation economics, it encompasses all forms of individual movement toward a destination, regardless of motive or mode, even including walking. In urban logistics, it refers to the full spectrum of actions aimed at facilitating the movement of people within a given area (Gdowska et al., 2018). At its core, mobility is an expression of human activity, driven by two fundamental decisions: whether to travel and how to travel, including the choice of mode, timing, and route. These decisions are influenced by an interplay of external factors, such as infrastructure availability and economic considerations, as well as internal factors, including personal preferences, social influences, and psychological perceptions. Despite growing environmental awareness, the car remains a potent symbol of success and wealth; its cultural status frequently overshadows considerations of efficiency and sustainability. Such dynamics have fostered a car-centric mobility culture that not only exacerbates congestion – by inefficiently using limited road space – but also diminishes the attractiveness of alternative modes such as public transport.

The adverse effects of traditional, car-based mobility have prompted widespread public concern over worsening traffic conditions, inadequate safety, and declining urban quality of life due to increased noise, emissions, and spatial constraints. In response, cities are increasingly embracing a "new mobility culture" that seeks to reconcile economic growth with social well-being and environmental sustainability. This emerging paradigm emphasizes reducing private car use in favor of collective transport solutions and transitioning away from fossil-fuel-powered vehicles toward those powered by renewable energy or even human effort, as evidenced by initiatives such as Sustainable Urban Mobility Plans in Polish cities. The combined pressures of urbanization and advances in communication technologies have catalyzed new trends in urban mobility (Książek et al., 2021). Consumers are now more inclined toward services such as vehicle rentals, ride-sharing, and multimodal transportation, all of which have been facilitated by mobile applications. Although these trends initially took root in the United States and Western Europe, they are also rapidly gaining traction in Poland.

Two key concepts – the sharing economy and ecomobility – have become central to contemporary discussions on urban mobility. The sharing economy, with its emphasis on the on-demand use of resources rather than ownership, has deepened its influence in the transport sector. The availability of ride-hailing services (e.g., Uber or Lyft), carpooling platforms (e.g., BlaBlaCar, Zimride), and both public and private car-sharing systems demonstrates how shared mobility can optimize vehicle usage and alleviate congestion (Korcyl et al., 2016). In contrast, ecomobility represents a broader challenge to the automotive industry. It is not merely about eco-friendly transport; it is about rethinking mobility to offer fast, affordable, and reliable transportation while minimizing environmental impact.

In Poland, the drive toward ecomobility is supported by public innovation funds and targeted programs from institutions such as the National Fund for Environmental Protection, the National Centre for Research and Development, and the Polish Development Fund. These state-driven initiatives aim to establish the technical and organizational foundations that will make ecological transport options the natural choice for the public. Taken together, the evolution of urban mobility in Poland is marked by a gradual yet significant shift away from outdated, car-dependent paradigms toward a more balanced and sustainable system – one that integrates shared mobility and ecomobility to address the spatial, social, and economic challenges of modern cities.

Finally, the adoption of EVs is shaped not only by technology and policy but also by consumer perceptions and social acceptance. Beyond technical and economic considerations, the social dimension of electromobility adoption is critical. Consumer surveys highlight persistent barriers, including range anxiety, limited awareness of the total cost of ownership, and the perception that EVs are luxury products accessible only to wealthier households (Sierzchula et al., 2014; Sovacool et al., 2018). Addressing these concerns requires targeted educational campaigns, transparent communication of lifecycle costs, and visible municipal initiatives that promote the normalization of EV use in public fleets and shared mobility services. Such measures can enhance consumer confidence and accelerate the diffusion of EVs by reframing them as mainstream mobility solutions rather than niche alternatives.

6. CONCLUDING REMARKS

This study has demonstrated that adopting electromobility in Poland entails complex trade-offs among costs, infrastructure, and environmental outcomes. By explicitly framing these trade-offs as decision-making challenges, the paper contributes to the decision sciences in three ways: (1) it structures the electromobility adoption problem as a multi-stakeholder decision under uncertainty; (2) it highlights the role of policy, managerial, and consumer perspectives in shaping feasible strategies; and (3) it provides empirical cost-benefit and infrastructure analysis to support informed choices. The transition to sustainable transport is not merely technological, but decisional, requiring adaptive strategies across consumers, firms, and governments.

The rapid development of electromobility – both globally and in Poland – offers a vital response to the environmental challenges posed by combustion-engine transportation. Electric vehicles provide a sustainable alternative for public and private transportation, benefiting both society and the natural environment. Historically, the automotive and electric power sectors operated independently, with little overlap.

Today, EVs bridge that gap by not only enabling eco-friendly transportation but also providing the potential to store energy during periods of peak demand. As major manufacturers increasingly focus on electric and hybrid models, consumers can look forward to a broader range of options across various market segments.

EVs stand out for their low noise emissions, the near absence of harmful pollutants, and high torque levels that contribute to enhanced active safety. However, significant barriers to widespread adoption remain – namely, high upfront costs and an insufficiently developed charging infrastructure. In response, Poland introduced the "Electromobility Development Plan" in 2016, emphasizing improvements to charging infrastructure and a gradual reduction in vehicle costs. While EV sales in Poland have seen modest growth, many potential buyers still associate these vehicles with high technological sophistication and environmental consciousness, often overlooking the lower operating costs. Despite current high purchase and maintenance expenses, economies of scale and technological advances are expected to reduce production costs – especially in the compact and mini segments – making EVs increasingly accessible.

Looking ahead, the prospects for electromobility in Poland are promising. As production scales up and technological innovations continue, electric vehicles are poised to become a genuine alternative to combustion engine cars. These advancements will enhance affordability and broaden consumer appeal, ultimately leading to a cleaner, quieter, and more efficient urban mobility landscape.

REFERENCES

Bloomberg New Energy Finance (2017). *Lithium-ion battery costs and market outlook.* **URL:** https://about.bnef.com/ [16.12.2021].

Chłopek Z. (2002). *Ochrona środowiska naturalnego. Pojazdy samochodowe.* Wydawnictwa Komunikacji i Łączności, Warszawa.

Denis A. & Kuczyński W. (2017). Analiza porównawcza wpływu na środowisko aut elektrycznych zasilanych z elektrowni węglowych oraz aut spalinowych. *Autobusy*, **7–8**, pp. 61–64. **URL:** https://bibliotekanauki.pl/articles/316994.pdf [16.12.2021].

Edge J.S., O'Kane S., Prosser R., Kirkaldy N.D., Patel A.N., Hales A., Ghosh A., Ai W., Chen J., Yang J., Li S., Pang M.-C., Bravo Diaz L., Tomaszewska A., Marzook M.W., Radhakrishnan K.N., Wang H., Patel Y., Wu B. & Offer G.J. (2021). Lithium-ion battery degradation: What you need to know. *Physical Chemistry Chemical Physics*, **23**(14), pp. 8200–8221. **DOI:** https://doi.org/10.1039/D1CP00359C.

European Alternative Fuels Observatory (2020). Roads. Country fiches – Czech Republic, Hungary. **URL:** https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road/ [16.12.2021].

European Environment Agency (2019). *EMEP/EEA air pollutant emission inventory guidebook 2019: Technical guidance to prepare national emission inventories.* **URL:** https://www.eea.europa.eu/publications/emep-eea-guidebook-2019 [16.12.2021].

Flasza J. (2017). Elektromobilność w Polsce – wyzwania i możliwości z uwzględnieniem inteligentnych instalacji OZE. *Autobusy*, **30**(6), pp. 1196–1198. **URL:** https://yadda.icm.edu.pl/baztech/element/bwmeta1.element.baztech-3b3b4308-ac5c-4a3e-ad8a-21ac33b04b04?q=bwmeta1.element.baztech-e687c8e6-d61e-4483-abfd-7305024c9880;235&qt=CHILDREN-STATELESS [3.10.2021].

Flasza J. & Matuszczyk P. (2018). Elektromobilność w Polsce a systemy OZE. *Przegląd Elektrotechniczny*, **94**(1), pp. 33–36. **DOI:** https://doi.org/10.15199/48.2018.01.09.

Forum Energii (2021). *Transformacja energetyczna w Polsce – edycja 2021*. **URL:** https://www.forum-energii.eu/transformacja-energetyczna-w-polsce-edycja-2021 [16.12.2021].

Frankel D. & Wagner A. (2017). *Battery storage: The next disruptive technology in the power sector*. McKinsey & Company. **URL:** https://www.mckinsey.com/capabilities/sustainability/our-insights/battery-storage-the-next-disruptive-technology-in-the-power-sector [16.12.2021].

Gdowska K. (2018). How to assess balancing public transportation. In: *14th International Conference on Industrial Logistics, ICIL 2018 – Conference Proceedings*, Ben-Gurion University, Beer-Sheva, pp. 79–86. **URL:** https://in.bgu.ac.il/en/engn/iem/ICIL2018/Pages/ICIL%20conference%20proceedings%20book%202018.pdf [16.12.2021].

Gdowska K., Viana A. & Pedroso J.P. (2018). Stochastic last-mile delivery with crowdshipping. *Transportation Research Procedia*, **30**, pp. 90–100. **DOI:** https://doi.org/10.1016/j.trpro.2018.09.011.

International Energy Agency (2017). *Global EV Outlook 2017: Two million and counting*. **URL:** https://www.iea.org/reports/global-ev-outlook-2017 [16.12.2021].

International Energy Agency (2020). *Global EV Outlook 2020: Entering the decade of electric drive?* **URL:** https://www.iea.org/reports/global-ev-outlook-2020 [16.12.2021].

Jaguemont J., Boulon L. & Dubé Y. (2016). A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. *Applied Energy*, **164**, pp. 99–114. **DOI:** https://doi.org/10.1016/j.apenergy.2015.11.034.

Korcyl A., Książek R. & Gdowska K. (2016). A MILP model for the route optimization problem in a municipal multi-landfill waste collection system. In: *13th International Conference on Industrial Logistics, ICIL 2016 – Conference Proceedings*, AGH University of Science and Technology, Krakow, pp. 109–118. **URL:** http://www.icil.zarz.agh.edu.pl/images/ICIL2016/ICIL2016_conference_proceedings_final.pdf [16.12.2021].

Krawiec S. & Krawiec K. (2017). Rozwój elektromobilności w Polsce. Uwarunkowania, cele i bariery. *Studia ekonomiczne. Zeszyty Naukowe Uniwersytetu Ekonomicznego w Katowicach*, **332**, pp. 17–24.

Książek R., Gdowska K. & Korcyl A. (2021). Recyclables collection route balancing problem with a heterogeneous fleet. *Energies*, **14**(21), 7406. **DOI:** https://doi.org/10.3390/en14217406.

Kucharska A. & Ruszel M. (2016). Potencjał sektora elektromobilności w Austrii i Szwajcarii – wnioski dla Polski. *Nowa Energia*, **4**(52), pp. 86–88. **URL:** https://www.instytutpe.pl/wp-content/uploads/2015/09/Potencja%C5%82-rozwoju_A.Kucharska_M.Ruszel.pdf [16.12.2021].

Motor/NAF (2021). *Motors rekkeviddetest vinter 2021: Tyskerne lader til ny kamp om elbiltronen*. **URL:** https://www.motor.no/elbil/motors-rekkeviddetest-av-elbiler-vinter-2021/193624 [16.12.2021].

NAF (Norges Automobil-Forbund) (2020). *NAF tester rekkevidde på elbil – nykommere overrasker*). **URL:** https://www.naf.no/elbil/bruke-elbil/test-rekkevidde-sommer-2020 [16.12.2021].

Polskie Sieci Elektroenergetyczne (2021). *Raport 2020 KSE: Zestawienie danych ilościowych dotyczących funkcjonowania KSE w 2020 roku*. **URL:** https://www.pse.pl/dane-systemowe/funkcjonowanie-kse/raporty-roczne-z-funkcjonowania-kse-za-rok/raporty-za-rok-2020 [16.12.2021].

Polskie Stowarzyszenie Nowej Mobilności (2021). *Licznik elektromobilności: listopad 2021 rekordowym miesiącem w polskiej elektromobilności*. **URL:** https://psnm.org/2021/informacja/licznik-elektromobilnosci-listopad-2021-rekordowym-miesiacem-w-polskiej-elektromobilnosci/ [16.12.2021].

Sierzchula W., Bakker S., Maat K. & van Wee B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, **68**, pp. 183–194. **DOI:** https://doi.org/10.1016/j.enpol.2014.01.043.

Sipiński D. & Bolesta K. (2017). *Cicha rewolucja w energetyce. Elektromobilność w Polsce*. „Polityka Insight", Warszawa. **URL:** https://www.politykainsight.pl/_resource/multimedium/20106685 [16.12.2021].

Sovacool B.K., Axsen J. & Kempton W. (2018). The future promise of vehicle-to-grid (V2G) integration: A sociotechnical review and research agenda. *Annual Review of Environment and Resources*, **42**, 1–25. **DOI:** https://doi.org/10.1146/annurev-environ-030117-020220.

United Nations Climate Change (2015). *The Paris Agreement*. **URL:** https://unfccc.int/process-and-meetings/the-paris-agreement [3.10.2021].

Ustawa z dnia 11 stycznia 2018 r. o elektromobilności i paliwach alternatywnych (Dz.U. 2018 poz. 317).

Wasiak I., Błaszczyk P. & Wojciechowska K. (2014). Tendencje rozwoju aut elektrycznych w Unii Europejskiej. *Logistyka*, **3**, pp. 6591–6598.

Wiśniowski W. (2018). *Analiza zmian mobilności miejskiej związanych z rozwojem rynku samochodów elektrycznych*. Master's Thesis. AGH University of Science and Technology, Faculty of Management, Krakow, Poland.

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How to Interpret AHP/ANP Application Results in a Really Meaningful Manner?

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Abstract. Final decision recommendations rely heavily on ranking Decision-Making Units (DMUs), often achieved using Saaty's Analytic Hierarchy/Network Process (AHP/ANP). AHP/ANP provides precise overall priority scores which decision-makers commonly treat as definitive for ranking purposes. This reliance means that even minimal numerical differences between DMUs are used to determine the final selection. However, this strict adherence to tiny numerical distinctions – disregarding the actual degree of difference – is problematic. Practically, it risks rejecting DMUs whose performance is only slightly inferior; methodologically, it contradicts the qualitative nature of the input (pairwise comparisons) with the quantitative output. This tension raises the question of achieving an adequate qualitative interpretation of the quantitative rankings. To resolve this, the paper proposes clustering approaches to help decision-makers reliably group and discriminate among similar DMUs. These methods aim to justify more informed choices by avoiding spurious precision. The approaches were tested using two diverse decision cases. The results are promising and indicate that these clustering techniques can be useful under certain specific circumstances.

Keywords: decision analysis, AHP/ANP, results, interpretation, compatibility, qualitative

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1. INTRODUCTION

The application of the multi-attribute decision analysis (MADA) methodology provides decision makers with recommendations that facilitate actual decision making. The methodology is implemented by means of diverse techniques. The application of

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the techniques results in specific outcomes. One of the most popular forms of such outcomes is the ranking of considered alternatives (decision making units – DMUs). This is because a ranking represents an easily interpretable hierarchy of DMUs.

Analytic Hierarchy/Network Process (AHP/ANP) is one of the most popular MADA ranking techniques. It was initially developed by Saaty (1980) in the 1970s as the Analytic Hierarchy Process (AHP), and it was later extended to a more general approach, namely the Analytic Network Process (Saaty, 1996), in the 1990s. Both aforementioned flavors of the technique are based on the application of the same notion of pair-wise comparison. However, they differ in the actual character of fundamental inquiry regarding the differences between the compared DMUs. It is questionable how much two DMUs differ concerning their importance for actually achieving the fundamental analysis goal in AHP, while it is also queried how much they differ according to their influence on achieving that goal in ANP. The flavors also differ in applicable forms of relations between components (and component groups) in a model of a decision making problem.

The application of pair-wise comparison makes AHP/ANP capable of considering both qualitative and quantitative DMU attributes. The 9-point Saaty's scale is applied to provide the necessary means for the qualitative assessment of different DMUs being compared in a pair-wise manner. Subsequent integer numbers from 1 to 9 are utilized to express successive scale levels. A lack of difference in the compared DMUs with regard to their importance/influence corresponds with number 1. The following odd numbers: 3, 5, 7, and 9 express a gradual rise in the assessment of the difference – from a slight difference to an extreme difference. The even numbers: 2, 4, 6, and 8 are used to consider the hesitation regarding which adjacent scale level to choose, e.g., 6 instead of 5 or 7. Note that Saaty's scale levels from 2 to 9 directly conform to the advantage of the first compared DMU. Adequate reciprocal values, i.e., 1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, and 1/9, are applied in the case of a need to express the advantage of the second compared DMU.

It is obvious, therefore, that Saaty's scale application provides the AHP/ANP procedure with qualitative assessments that are expressed by numbers. The numbers are used directly to derive the overall priorities of DMUs and to construct the final hierarchy of DMUs. Unfortunately, despite the generally qualitative character of the input data provided by pair-wise comparisons, the outcomes of AHP/ANP technique application are commonly analyzed in a strictly numerical way. Therefore, this interpretation of the outcomes of AHP/ANP application seems to be incompatible with the actual qualitative nature of the technique.

It ultimately seems that the grouping of DMUs according to their overall priority is particularly well suited to provide suitable means for an adequate and meaningful interpretation of AHP/ANP application results. This is because it would be capable of both distilling sure top DMUs and enriching AHP/ANP use by means of the identification of close DMUs.

Note that there is an AHP-based approach, AHP Sort (Ishizaka et al., 2012), available to group DMUs. The approach also makes use of overall priorities to accomplish this. However, it requires the user to provide information about the subjective limiting profiles of DMUs classes, which are ultimately applied to group DMUs. It nevertheless seems that, in general, the application of predefined classes is not really necessary. This is because the mere application of overall priorities seems to provide all the necessary means to group DMUs while avoiding the influence of superfluous subjectivity.

The rest of the paper is structured in the following way, therefore. The second section is devoted to the discussion of selected approaches to sorting DMUs. The effects of their sample applications are discussed in the third section. The last section is devoted to some conclusions and final remarks.

2. GROUPING AHP/ANP RESULTS

AHP/ANP provides contextual results as vectors of overall DMU priorities. One-dimensional grouping could be applied, therefore, to divide DMUs that are close enough in terms of their overall priorities into common clusters. There are diverse one-dimensional tools available and some of them are presented in the following subsections.

2.1. Clustering tools

Clustering tools are capable of dividing objects that are described by several attributes into groups – clusters. Individual objects are assigned to the clusters that consist of the most similar objects to them. A concrete metric is applied to express the similarity of the objects. The metric is usually based on a concept of distance between points that represent DMUs in a multi-dimensional space of attributes. The smaller the distance between them, the more similar the corresponding DMUs are. Criteria of diverse kinds are applied when assigning objects to clusters. The criteria may operate on different concepts of cluster similarity provided by appropriate definitions of the distance between clusters. It is also possible to use measures involving the application of statistical concepts, such as extreme distance and the standard deviation of the distance between cluster components, etc. As a result, diverse procedures are available to group objects.

The simple gradient technique is based on the concept of the partition approach. Therefore, its procedure starts with one large cluster that contains all DMUs. It is then divided in a step by-step manner. The actual division deals with a sequence of overall priorities that is gradually partitioned at points of the currently largest difference between the overall priorities. Unfortunately, the stopping criterion depends on somewhat subjective information. A predefined number of distinct clusters (k) or a threshold of absolute difference (ϑ) between overall priorities may be applied in this regard. Note that the simple gradient procedure follows the idea of partitioning a minimum spanning tree (Florek et al., 1951), which is directly expressed by the overall ranking of DMUs.

The Szczotka–Spaeth (Spaeth, 1973; Szczotka, 1972) technique represents another concept: the aggregative approach. Its procedure starts with the initial division of DMUs into n clusters, where n is the number of DMUs. Hence, each initial cluster consists of precisely one DMU. The technique also belongs to optimization approaches, as it uses a goal function as a clustering criterion. The goal function addresses the minimization of the sum of the average distances between the components of distinct clusters. It looks as follows:

$$Q = \sum_{i=1}^{k} \frac{2}{n_i(n_i - 1)} \sum_{s,t=1}^{n_i} d_{st} \tag{1}$$

where n_i is the cardinality of the i-th consecutive DMU cluster, and d_{st} is distance between different DMUs, denoted by indices s, t ($s \neq t$), which are components of the i-th consecutive cluster.

Initial clusters are then gradually aggregated to compose more complex clusters in a step by-step manner. The effects of the integration of adjoining DMU clusters on the goal function value (1) is taken into account during each step. Hence, in each step, two adjoining clusters are selected to join. The actual choice of joined clusters corresponds to the smallest increase in the goal function (1) caused by cluster integration. As in the case of the simple gradient technique, the stopping criterion deals with achieving a DMU partition that contains a predefined number of k clusters. However, unlike the simple gradient approach, the technique belongs to aggregation methods. Note that the application of the Szczotka–Spaeth technique involves rather laborious calculations that require software support.

Both above mentioned techniques belong to hierarchical approaches. They are capable, therefore, of providing a cluster hierarchy whose levels define possible DMU partitions without the need to provide any stopping criterion. This is because their procedure stops just after the full cluster hierarchy is derived. Therefore, they are applied in such a way in the paper.

2.2. Other selected approaches

As can be seen from the previous subsection, the applicability of a clustering approach to identifying DMU groups may depend on additional subjective information or relatively complex and time consuming calculations. It seems purposeful, therefore, to try to identify a simple yet reliable one-dimensional clustering approach for AHP/ANP application results.

Let us first try to take advantage of the common 80/20 Pareto principle. It could be readily applied in the case of using AHP/ANP ideals in place of the raw overall DMU priorities. The ideal result from the transformation of overall priorities is that the highest DMU overall priority becomes equal to one. The priorities of other DMUs are then recalculated accordingly. The application of the Pareto rule would allow us to identify the closest DMU, i.e., the ones whose current ideals are contained within a 20% margin from the ideal for the top DMU, i.e., in the [0.8, 1] interval. As a result, all such DMUs would also be regarded as the topmost ones. They would also be excluded from further analysis due to the reduction of the DMUs set to obtain the set of currently active DMUs. Further analysis would involve the step-wise identification of top DMU from the currently active DMUs, as well as a step-wise reduction of the active DMU set until it becomes empty. Hence, Pareto rule-based procedure would finish without any need for subjective user's intervention. Note that the ideals for the currently active DMU must be updated in the beginning of each step to make the ideal for the top active DMU equal to one.

The Pareto rule exploits the constant threshold value $\vartheta = 0.80$. Note that it could nevertheless matter for the sake of the reliability of active DMU discrimination whether the threshold is constant or not. For example, Opricovic (1988) proposed using a threshold-based rule related to the actual number of DMU set to provide evidence of a significant and necessary advantage of a DMU over another DMU in the VIKOR technique (Opricovic & Tzeng, 2004). The evidence is based on the following ideal advantage threshold:

$$\varsigma = 1/(N - 1) \tag{2}$$

where: N denotes number of DMUs.

The threshold could be used in the same way as a 20% margin threshold in the case of Pareto rule application, with N denoting the number of current active DMUs. Therefore, a certain DMUs would prove to be very close to the topmost one if its current ideal were at least equal to:

$$\vartheta = 1 - \varsigma \tag{3}$$

The application of ϑ causes both rule-based procedures to stop immediately after the set of currently active DMUs becomes empty. However, the subsequent clusters are identified in a sequence from the best down to the worst DMUs. Hence, in the case the worst DMU is too far from the adjoining DMUs, what would imply $N = 1$ during the last procedure step, no further proceeding is actually needed, as it is obvious that the DMU would comprise a distinct cluster.

2.3. Partition validity

To facilitate the comparison of the effects of applying different DMU grouping approaches, additional methods for assessing the obtained DMU partitions should be utilized. There are many partition quality assessment indices available (Kolenda, 2006). The most popular means for partition quality checking is provided, however, by the silhouette coefficient $s(i)$ (Kaufman & Rousseeuw, 1990). t is a type of higher is better index. Its value for the i-th consecutive DMU would be described by the following equation:

$$s(i) = (b_i - a_i)/max(a_i, b_i), \tag{4}$$

where: a_i denotes average distance between the i-th consecutive DMU and other DMUs from the same cluster; b_i is the smallest average distance of the i-th consecutive DMU from DMUs in other clusters i.e. the average distance from the closest cluster (note that average linkage is applied with this regard in the paper, although any of possible linkage types maybe applied).

Silhouette coefficient values belong to the interval $[-1, +1]$. Its negative values would indicate that the DMU does not fit a given cluster. The better the i-th consecutive DMU fits a given cluster, the closer the coefficient $s(i)$ value is to $+1$. Note that the coefficient equals zero for a DMU that comprises a cluster itself. For the sake of simplicity, it is nevertheless assumed in the paper that the existence of single DMU clusters does not influence the quality of a partition at all.

It is generally accepted that $s(i)$ values above 0.71 indicate very high partition quality, and levels above 0.51 signify good quality for the partition from the perspective of the i-th consecutive object. The latter value is therefore ultimately associated in the paper with a notion of acceptable fit for the i-th consecutive DMU.

3. SAMPLE ANALYSIS

3.1. Sample data

The results of two sample AHP/ANP applications are used to present the potential merits and drawbacks of the aforementioned grouping approaches. The applications differ in the number of DMUs, making it possible to examine the effects of different conditions. The first case deals with a rather mean number of DMUs. It pertains to the ranking of sustainability programs of six Brazilian textile industry companies. The programs are denoted by the symbols E1–E6. Overall priorities for the programs are given in Table 1.

Table 1. *Overall priorities of sustainability programs in textile industry (Netto et al., 2021)*

Sustainability program	E2	E5	E3	E1	E6	E4
Overall priority	0.64	0.52	0.38	0.36	0.28	0.26
Ideal	1	0.813	0.594	0.563	0.438	0.406
Rank	1	2	3	4	5	6

The second case pertains to the results of a recent AHP application for ranking 16 Polish voivodships concerning their biogas technology potential (Ginda & Szyba, 2020). Overall priorities and ideals obtained for the voivodeships are presented in Table 2.

Table 2. *The results of AHP application (Ginda & Szyba, 2020)*

Rank	DMU	Overall priority	Ideal	Rank	DMU	Overall priority	Ideal
1	B	0.1820	1	2	N	0.1701	0.9346
3	W	0.1648	0.9054	4	L	0.1623	0.8917
5	Z	0.1437	0.7895	6	F	0.1384	0.7604
7	P	0.1019	0.5598	8	T	0.0828	0.4549
9	O	0.0797	0.4379	10	E	0.0681	0.3741
11	C	0.0673	0.3697	12	S	0.0647	0.3554
13	R	0.0624	0.3428	13	G	0.0624	0.3428
15	D	0.0615	0.3379	16	K	0.0524	0.2879

3.2. The case of six DMUs

Let us use information about priority difference ranks in a simple gradient approach. We start from the establishment of a global cluster of all DMUs: {E2 E5 E3 E1 E4 E6}. The largest priority difference is then applied to define the initial partition point. It is clear from Table 1 that the largest priority difference corresponds to the gap between E5 and E3 sustainability programs. We end up, therefore, with two second level clusters in the first step. The first cluster consists of E2 and E5 programs while the second one contains the remaining programs. The application of next priority differences in descending order allows us to complete levels of the cluster hierarchy. The hierarchy is presented in Table 3. We can see that there are 6 final clusters in the bottommost hierarchy level. Three intermediate hierarchy levels correspond to the partitions with two, three, and four distinct clusters, respectively.

Table 3. *Cluster level hierarchy for simple gradient technique application*

Cluster hierarchy level	Partition
Top	{E2 E5 E3 E1 E6 E4}
sg26	{E2 E5}={E3 E1 E6 E4}
sg36	{E2}={E5}={E3 E1 E6 E4}
sg46	{E2}={E5}={E3 E1}={E6 E4}
Bottom	{E2}={E5}={E3}={E1}={E6}={E4}

Now is the time to make a decision about which partition expresses the best division of sustainability programs. For example, we could prefer having no more than 4 clusters or aim to achieve a similarity measure at a level not higher than an average priority difference (0.76 in this case). It proves, therefore, that we could finally be happy with the sg46 partition given by the fourth cluster level. The partition deals with the division of sustainability programs into four distinct clusters. Two of them consist of a single program (E2 or E5), and the two remaining clusters consist of two programs each: {E3 E1}, and {E6 E5}. Let's take a look at the $s(i)$ values to ensure the quality of the partitions from Table 3.

Individual silhouette coefficient values (see Table 4) obtained for sg26 support the following conclusions:

1. E2 sustainable strategy would fit rather well with a common cluster shared with E5 sustainable strategy. However, a rather low $s(i)$ coefficient value for E5 strategy suggests that it doesn't fit the cluster well. Therefore, it finally turns out that both aforementioned strategies should comprise distinct clusters in their own right.
2. Coefficient values for the remaining strategies suggest that they either fit very well (E6, E4) or fit well (E1, E3) within their common cluster.

We can also see a considerable drop in $s(i)$ values for the worst four strategies after the two top strategies were separated into two distinct clusters (see sg36 partition in Table 3). Such a decrease in the coefficient values suggests that the

E3, E1, E6, and E4 strategies no longer fit the common cluster well. The considerable increase in the coefficient following their division into two separate clusters confirms the superiority of the sg46 partition in the case of the simple gradient approach application.

Table 4. *Silhouette coefficient values s(i) for the partitions – the simple gradient approach application case*

Partition	E2	E5	E3	E1	E6	E4
sg26	0.625	0.4	0.6	0.697	0.778	0.75
sg36	–	–	0.429	0.583	0.722	0.692
sg46	–	–	**0.818**	**0.778**	**0.778**	**0.818**

Let us now apply the Szczotka–Spaeth technique. The anticipated effects of grouping the adjoining distinct sustainability strategies are tested according to the goal function Q (1), and a new cluster that minimizes the current goal function as much as possible is recorded in each step. Hence, cluster hierarchy emerges in a step-wise manner. The results of consecutive steps are presented in Tables 5–8. Note that the recommended clusters are expressed there by means of boldface. The calculations result in a cluster hierarchy, one which is finally presented in Table 9.

The comparison of cluster hierarchies obtained through the application of the simple gradient approach (Table 3) and the application of the Szczotka–Spaeth technique (Table 9) reveals a difference. The difference is associated with two unique partitions. The first one (ss56) corresponds with the second cluster hierarchy level and consists of one cluster, which comprises two components {E3 E1}, as well as four clusters that contain a single component each: {E2}, {E5}, {E6}, and {E4}. The second partition (ss26) is presented in the fifth cluster hierarchy level and consists of a single component cluster {E2} and a cluster that is composed of the remaining sustainability programs. We finally use silhouette coefficient values again to justify the partition – see Table 10 for details.

Table 5. *The effects of possible joining of adjoining sustainability programs after the initial step of Szczotka–Spaeth technique*

Possible new cluster	{E2 E5}	{E5 E3}	**{E3 E1}**	{E1 E6}	{E6 E4}
$\boldsymbol{Q}$ **(1)**	0.12	0.14	**0.02**	0.08	0.02

Table 6. *The effects of possible joining of adjoining sustainability programs after the second step of Szczotka–Spaeth technique*

Possible new cluster	{E2 E5}	{E5 E3 E1}	{E3 E1 E6}	**{E6 E4}**
$\boldsymbol{Q}$ **(1)**	0.14	0.126	0.087	**0.04**

Table 7. *The effects of possible joining of adjoining sustainability programs after the third step of Szczotka–Spaeth technique*

Possible new cluster	{E2 E5}	{E5 E3 E1}	**{E3 E1 E6 E4}**
***Q* (1)**	0.16	0.127	**0.073**

Table 8. *The effects of possible joining of adjoining sustainability programs after the fourth step of Szczotka–Spaeth technique*

Possible new cluster	{E2 E5}	**{E5 E3 E1 E6 E4}**
***Q* (1)**	0.193	**0.124**

Table 9. *Cluster hierarchy levels – the application of Szczotka–Spaeth technique*

Cluster hierarchy level	Partition
Top	{E2 E5 E3 E1 E6 E4}
ss26	**{E2}={E5 E3 E1 E6 E4}**
ss36=sg36	{E2}={E5}={E3 E1 E6 E4}
ss46=sg46	{E2}={E5}={E3 E1}={E6 E4}
ss56	**{E2}={E5}={E3 E1}={E6 E4}**
Bottom	{E2}={E5}={E3}={E1}={E6}={E4}

Table 10. *Silhouette coefficient values s(i) for the unique partitions according to Szczotka–Spaeth technique*

Cluster hierarchy level	E2	E5	E3	E1	E6	E4
ss26	–	–	**0.8**	**0.75**	–	–
ss56	–	−0.4	0.635	0.679	0.694	0.671

Hence, it is clear that the use of the partition from the fifth cluster hierarchy level ss56 is inefficient due to the negative coefficient value for the E5 sustainability program, which indicates a total mismatch for the program. It also turns out that the application of a unique partition ss26 would result in lower coefficient values for E3 and E1 sustainability programs than those obtained for partition sg46 in the case of the simple gradient approach – see Tables 3 and 4. It seems, therefore, that it should be rejected in favor of the third cluster hierarchy level partition presented in Table 9, which is identical to the sg46 partition from Table 3. Hence, his final partition recommendation is the same as in the case of using the simple gradient approach.

The use of the Pareto-based rule is grounded in the application of ideals obtained for the sustainability programs (see Table 1). The results of the conducted calculations are illustrated in Table 11. We start from core ideals and the fully active DMU set. The second best DMUs (E5) has an ideal within a 2% margin of the topmost DMU, while the ideals of other DMUs are outside the margin. Hence, the topmost cluster consists of two top sustainability programs, E2 and E5. We remove them from the set of active DMUs and proceed with the remaining four sustainability programs. The ideal for the best of the remaining programs is then scaled to 1, and the ideals of the other active sustainability programs are recalculated accordingly. The current ideal for the second most active DMU (E1) fits a 20% margin from the current top active DMU (E3). Hence, the second topmost cluster consists of two sustainability programs: E3 and E1. The same conclusion pertains to the bottommost cluster, which consists of the remaining DMUs: E6 and E4. Hence, the application of the Pareto-based rule for clustering results in a unique set of three double sized clusters. Individual silhouette coefficient values for the partition are presented in Table 12.

Table 11. *Pareto rule-based approach illustration ($\vartheta = 0.80$) for the six DMUs case*

Step I		Step II		Step III	
Sustainability program	Ideal	Sustainability program	Ideal	Sustainability program	Ideal
E2	**1**	–	–	–	–
E5	**0.81**	–	–	–	–
E3	0.59	**E3**	**1**	–	–
E1	0.56	**E1**	**0.94**	–	–
E6	0.43	E6	0.73	**E6**	**1**
E4	0.40	E4	0.68	**E4**	**0.92**

Table 12. *Silhouette coefficient values s(i) for the unique partition {E2 E5} {E3 E1} {E6 E4}*

E2	E5	E3	E1	E6	E4
0.555	0.2	0.8	0.6	0.778	0.818

The contents of Table 12 confirm that the final partition provided by the application of the Pareto rule-based approach is slightly better than some other partitions obtained through the application of different clustering approaches (e.g., the sg26 partition in Table 3) from the perspective of clearly less preferred sustainability programs E3, E1, E6, and E4. It is, nevertheless, unacceptable because the sustainability program E5 does not fit the partition at all.

Let us finally use a VIKOR-like marginal approach. The results of the calculations are illustrated in Table 13. The first step deals with all sustainable programs and their original ideals again. This time, however, the margin from the topmost DMU depends on the current cardinality of the initial active DMU set. The cardinality is equal to $N = 6$. Hence, according to (2) the initial threshold yields: $\vartheta = 0.80$. he application of the threshold results in the same topmost cluster structure as in the case of applying the Pareto-rule {E2 E5}. The second step deals with a reduced set of four active DMUs. The current margin from the topmost active DMU is therefore calculated for $N = 4$, therefore. It yields $\vartheta = 0.67$, now. The ideals of all four active DMUs qualify them for the second highest cluster {E3 E1 E6 E4}. The procedure stops, therefore, all DMUs have been distributed among clusters. Note that the obtained partition is the same as the inefficient sg26 partition in the second cluster hierarchy level (Table 3).

Table 13. *VIKOR-like rule-based approach illustration*

Step I		Step II	
N	ϑ	N	ϑ
6	0.80	4	0.67
Sustainability program	Ideal	Sustainability program	Ideal
E2	**1**	E2	–
E5	**0.81**	E5	–
E3	0.59	**E3**	**1**
E1	0.56	**E1**	**0.94**
E6	0.43	**E6**	**0.73**
E4	0.40	**E4**	**0.68**

The best partitions identified by means of the core application of all used approaches are presented in Table 14. Partitions delivered by the Pareto rule and VIKOR-like rule are unacceptable from the E5 sustainability program's point of view. It seems, therefore, that only clustering approaches may be capable of providing partitions in which all the sustainability programs fit well.

Table 14. *The best outcomes for use of applied approaches for the six DMUs case*

Approach	Partition	E2	E5	E3	E1	E6	E4
		$s(i)$					
Simple gradient Szczotka–Spaeth	**{E2}={E5}={E3 E1}={E6 E4}**	–	–	0.82	0.78	0.78	0.82
Pareto rule	{E2 E5}={E3 E1}={E6+E4}	0.56	0.20	0.80	0.60	0.78	0.82
VIKOR-like rule	{E2 E5}={E3 E1 E6 E4}	0.63	0.40	0.60	0.70	0.78	0.75

3.3. The case of sixteen DMUs

Cluster hierarchy levels that result from the application of a simple gradient technique in the case of biogas potential analysis are presented in Table 15. A statistical summary of the corresponding silhouette coefficient values $s(i)$ for all meaningful partitions is presented in Table 16.

Note that the partitions that make up the highest levels in the cluster hierarchy (sg2–sg7) correspond to minimal values of silhouette coefficients, which testify that some sustainability programs do not fit the partitions well. These are the eighth and ninth cluster hierarchy levels that define partitions (sg8, sg9) which guaranty a good fit for all sustainability programs. The advantage in mean and maximum silhouette coefficient values makes sg8 the final recommendation for the partition; however, Note that excellent silhouette coefficient values are obtained in the case of partitions from the twelfth and thirteenth cluster hierarchy levels. These partitions, nevertheless, seem to be unsuitable because they are extremely fragmented.

Table 15. *Cluster hierarchy – the simple gradient technique application case for sixteen DMUs case*

Name	Partition
Top	B+N+W+L+Z+F+P+T+O+E+C+S+G+R+D+K
sg2	B+N+W+L+Z+F P+T+O+E+C+S+G+R+D+K
sg3	B+N+W+L+Z+F P T+O+E+C+S+G+R+D+K
sg4	B+N+W+L Z+F P T+O+E+C+S+G+R+D+K
sg5	B N+W+L Z+F P T+O+E+C+S+G+R+D+K
sg6	B N+W+L Z+F P T+O E+C+S+G+R+D+K
sg7	B N+W+L Z+F P T+O E+C+S+G+R+D K
sg8	B N W+L Z F P T+O E+C+S+G+R+D K
sg9	B N W+L Z F P T O E+C+S+G+R+D K
sg10	B N W+L Z F P T O E+C S+G+R+D K
sg11	B N W L Z F P T O E+C S+G+R+D K
sg12	B N W L Z F P T O E+C S G+R+D K
sg13	B N W L Z F P T O E C S G+R+D K
Bottom	B N W L Z F P T O E C S G+R D K

Table 16. *Silhouette coefficient statistics for unique partitions for simple gradient technique application case for sixteen DMUs case*

Name	Number of clusters	**min** $s(i)$ (DMU)	mean $s(i)$	max $s(i)$ (DMU)	std.dev. $s(i)$ (DMU)
sg2	2	0.398 (P)	0.793	0.888 (D)	0.126
sg3	3	0.058 (T)	0.634	0.805 (R)	0.229
sg4	4	0.058 (T)	0.661	0.831 (F)	0.210
sg5	5	0.058 (T)	0.665	0.806 (F)	0.221
sg6	6	0.450 (N)	0.712	0.838 (T)	0.118
sg7	7	0.450 (N)	0.722	0.832 (T)	0.096
sg8	**9**	**0.528 (W)**	**0.707**	**0.832 (T)**	**0.085**
sg9	**10**	**0.528 (W)**	**0.670**	**0.776 (S)**	**0.074**
sg10	11	0.133 (S)	0.668	0.850 (E)	0.224
sg11	12	0.133 (S)	0.689	0.850 (S)	0.251
sg12	**13**	**0.719 (D)**	**0.776**	**0.804 (G,R)**	**0.040**
sg13	**14**	**0.719 (D)**	**0.776**	**0.804 (G,R)**	**0.040**

Table 17 presents the cluster hierarchy obtained through the application of the Szczotka–Spaeth technique. The technique provides 5 partitions, which also appear in the simple gradient approach to the use-related cluster hierarchy. They include the most notable ones with regard to individual silhouette coefficient values as well. However, the majority of partitions provided by the technique are unique. The unique partitions are expressed in Table 17 by boldface. Silhouette coefficient statistics for them are given in Table 18.

Table 17. *Cluster hierarchy – Szczotka–Spaeth technique application case for sixteen DMUs case*

Name	Partition
Top	B+N+W+L+Z+F+P+T+O+E+C+S+G+R+D+K
sg2	B+N+W+L+Z+F P+T+O+E+C+S+G+R+D+K
ss3	**B+N+W+L Z+F P+T+O+E+C+S+G+R+D+K**
ss4	**B N+W+L Z+F P+T+O+E+C+S+G+R+D+K**
ss5	**B N+W+L Z F P+T+O+E+C+S+G+R+D+K**
ss6	**B N+W+L Z F P T+O+E+C+S+G+R+D+K**
ss7	**B N+W+L Z F P T O+E+C+S+G+R+D+K**
ss8	**B N+W+L Z F P T O E+C+S+G+R+D+K**
ss9	**B N W+L Z F P T O E+C+S+G+R+D+K**
ss10	**B N W L Z F P T O E+C+S+G+R+D+K**
ss11	**B N W L Z F P T O E+C+S+G+R+D K**
sg11	B N W L Z F P T O E+C S+G+R+D K
sg12	B N W L Z F P T O E+C S G+R+D K
sg13	B N W L Z F P T O E C S G+R+D K
Bottom	B N W L Z F P T O E C S G+R D K

Table 18. *Silhouette coefficient statistics for unique partitions for Szczotka–Spaeth technique application case for sixteen DMUs case*

Name	Number of clusters	min $s(i)$ (DMU)	mean $s(i)$	max $s(i)$ (DMU)	std.dev. $s(i)$ (DMU)
ss3	3	0.104 (P)	0.723	0.860 (S)	0.188
ss4	4	0.104 (P)	0.731	0.860 (S)	0.196
ss5	5	0.039 (P)	0.712	0.855 (S)	0.223
ss6	6	0.058 (T)	0.645	0.805 (G, R)	0.232
ss7	7	−0.818 (O)	0.505	0.773 (W)	0.430
ss8	8	0.450 (E)	0.651	0.773 (W)	0.127
ss9	9	0.455 (E)	0.642	0.771 (G, R)	0.114
ss10	10	0.455 (E)	0.653	0.771 (G,R)	0.120
ss11	**11**	**0.617 (E)**	**0.692**	**0.776 (S)**	**0.058**

It appears that almost all unique partitions derived from the application of the Szczotka–Spaeth technique deal with rather unacceptable silhouette coefficient values for individual DMUs. The only unique partition that provides acceptable values for the coefficient consists of a single cluster {E C S G R D} and 10 clusters made up of distinct DMUs. Coefficient values for individual DMUs seem, nevertheless, to suggest that the partition is slightly worse than the best partitions provided by the gradient approach application (see Table 16).

The sequence of the Pareto rule-based procedure steps is illustrated in Table 19. The boldfaced ideals in the table correspond to the current cluster composition. Note that the application of the procedure finally gives the partition, which consists of 5 clusters: {B N W L}, {Z F}, {P T}, {O E C S}, and {G R D K}. The silhouette coefficient values for individual DMUs, which are presented in the last column of Table 19, show, however, that the partition is inefficient (see the boldfaced entries in the last column). This is because some DMUs generally misfit the partition (T, S, O), while others show a rather poor fit (C, E, P, K).

Table 19. *Pareto rule-based approach use illustration (ϑ = 0.80) for the sixteen DMUs case*

DMU	I	II	III	IV	V	$s(i)$
B	**1**	–	–	–	–	0.603
N	**0.934**	–	–	–	–	0.713
W	**0.905**	–	–	–	–	0.649
L	**0.891**	–	–	–	–	0.529
Z	0.789	**1**	–	–	–	0.797
F	0.760	**0.963**	–	–	–	0.831
P	0.559	0.709	**1**	–	–	**0.402**
T	0.454	0.576	**0.812**	–	–	**–0.327**
O	0.437	0.554	0.782	**1**	–	**–0.027**
E	0.374	0.473	0.668	**0.854**	–	**0.375**
C	0.369	0.468	0.660	**0.844**	–	**0.309**
S	0.355	0.450	0.634	**0.811**	–	**–0.282**
G	0.342	0.434	0.612	0.782	**1**	0.519
R	0.342	0.434	0.612	0.782	**1**	0.519
D	0.337	0.428	0.603	0.771	**0.985**	0.570
K	0.287	0.364	0.514	0.657	**0.839**	**0.447**

The sequence of steps for the VIKOR-like rule-based application is presented in Table 20. The obtained results suggest a partition that consists of 7 clusters: {B N}, {W L}, {Z F}, {P}, {T O}, {E C S G R D}, and {K}. Although the partition is much better, in terms of the silhouette coefficient, than the partition resulting from the application of the Szczotka–Spaeth technique, it is still ineffective. This is due to an unacceptable coefficient value for the second best DMU and a rather poor value for the top DMU. It is truly a pity, as fairly high silhouette coefficient values are registered for the majority of the remaining DMUs.

The comparison of final results for the sixteen DMUs case is presented in Table 21. It transpires that the application of different approaches results in the identification of partitions that differ in the structure of DMU clusters. The number of clusters ranges from 5 in the case of the Pareto rule, application to 11 in the case of the Szczotka–Spaeth technique. Almost all the approaches proved capable of identifying partitions where more than half of the DMUs form clusters consisting of at least two DMUs. Szczotka–Spaeth is a notable exception in this regard.

Table 20. *VIKOR-like rule approach rule-based use illustration for the sixteen DMUs case*

DMU	I	II	III	IV	V	VI	VII	$s(i)$
N	16	14	12	10	9	7	1	
ϑ	0.067	0.077	0.091	0.111	0.125	0.167	–	
B	**1**	–	–	–	–	–	–	**0.355**
N	**0.934**	–	–	–	–	–	–	**–0.450**
W	0.905	**1**	–	–	–	–	–	0.778
L	0.891	**0.984**	–	–	–	–	–	0.818
Z	0.789	0.872	**1**	–	–	–	–	0.733
F	0.760	0.839	**0.963**	–	–	–	–	0.789
P	0.559	0.618	0.709	**1**	–	–	–	–
T	0.454	0.502	0.576	0.812	**1**	–	–	0.832
O	0.437	0.483	0.554	0.782	**0.962**	–	–	0.797
E	0.374	0.413	0.473	0.668	0.822	**1**	–	0.662
C	0.369	0.408	0.468	0.660	0.812	**0.988**	–	0.728
S	0.355	0.392	0.450	0.634	0.781	**0.950**	–	0.776
G	0.342	0.378	0.434	0.612	0.753	**0.916**	–	0.724
R	0.342	0.378	0.434	0.612	0.753	**0.916**	–	0.724
D	0.337	0.373	0.428	0.603	0.742	**0.903**	–	0.618
K	0.287	0.318	0.364	0.514	0.632	0.769	**1**	–

Table 21. *Final results for the sixteen DMUs case*

Approach (number of clusters)	**Partition**			
	min $s(i)$ (DMU)	**mean $s(i)$**	**max $s(i)$ (DMU)**	**std.dev. $s(i)$**
Simple gradient (9)	{B}={N}={W L}={Z}={F}={P}={T O}={E C S G R D K}			
	0.528 (W)	0.707	0.832 (T)	0.085
Szczotka–Spaeth (11)	{B}={N}={W}={L}={Z}={F}={P}={T}={O}={E C S G R D}={K}			
	0.617 (E)	0.692	0.776 (S)	0.058
Pareto rule (5)	{B N W L}={Z F}={P T}={O E C S}={G R D K}			
	−0.327 (T)	0.414	0.831 (F)	0.336
VIKOR-like rule (7)	{B}={N}={W L}={Z F}={P}={T O}={E C S G R D}={K}			
	−0.450 (N)	0.635	0.854 (G, R)	0.322

4. DISCUSSION

Results of the presented analysis show that traditional clustering approaches seem capable of indicating partitions that provide a good fit for individual DMUs. On the other hand, both proposed rule-based approaches seem to lack such a capability. A closer look at the results of the application of distinct techniques (see Table 14 and Table 21) nevertheless provides some hints regarding possible improvements in the results. For example, there is only a single E5 sustainability program that doesn't fit the final partition suggestion provided by the application of both rule-based approaches for the six DMUs case (see Table 14). Hence, we could try to break its common cluster with the E2 program (VIKOR rule-based partition only) or even merge it with the cluster of worse sustainability programs. The anticipated effects of these actions are presented in Table 22. The effects nonetheless confirm that the corrections result in unsatisfactory outcomes.

Table 22. *Anticipated effects of partition corrections for the six DMUs case*

Approach	Partition	$s(i)$					
		E2	E5	E3	E1	E6	E4
Pareto rule	{E2}={E5 E3 E1}={E6 E4}	–	−0.20	0.27	0	0.52	0.50
VIKOR-like rule	{E2}={E5}={E3 E1 E6 E4}	–	–	0.42	0.58	0.72	0.69
	{E2}={E5 E3 E1 E6 E4}	–	−0.40	0.63	0.67	0.69	0.67

Let us see if it is possible to improve the results of the application of rule-based approaches in the sixteen DMUs case. The contents of Table 19 suggest that the main problem with the inefficiency of the partition resulting from the application of the Pareto rule clearly pertains to the cluster {P T O E C S}. The somewhat poor, although not very bad, silhouette coefficient values for P, E, and C suggest that it could be advantageous to separate them into distinct clusters: {P} and {E C}. By the way, conducting the same action regarding the least preferable DMU, namely K, may also help improve individual silhouette coefficient values. Note that negative values for the coefficient in the cases of T and O also suggest that these DMUs could benefit from a common, distinct cluster. On the other hand, the negative silhouette coefficient value for S suggests that it would fit better into a common cluster with slightly better DMUs (C and E) and slightly worse DMUs (G, R, and D). Hence, we could finally obtain the corrected partition, which would consist of 6 clusters: {B N W L}, {Z F}, {P}, {T O}, {E C S G R D}, and {K}. The quality of the derived partition is confirmed by the contents of Table 23.

Table 23. *Recommended corrected partition for sixteen DMUs case – Pareto rule approach application*

Partition	min $s(i)$	mean $s(i)$	max $s(i)$	std.dev. $s(i)$
{B N W L}={Z F}={P}={T O}={E C S G R D}={K}	0.529 (L)	0.713	0.832 (T)	0.088

In the case of the VIKOR-like rule application (see Table 20), the presence of only two unsatisfactory values for individual silhouette coefficient values for adjacent top DMUs, B and N, seems to suggest a rather obvious and simple solution for improving the partition. The solution would address the final division of two top DMUs into two separate clusters or the final integration of N into the adjoining cluster {W L}. Note that the latter partition is identical to the sg7 partition from the seventh level of the cluster hierarchy obtained for the simple gradient approach application (see Table 15). Nevertheless, the descriptive statistics for individual silhouette coefficient values for the partition presented in Table 16 show that N fits rather poorly with the common cluster of W and L. The division of the two top DMUs among two distinct clusters is finally recommended. Therefore, the final recommended partition consists of 8 clusters. Note that the corrected partition is only slightly worse than the best partitions derived from the application of both clustering approaches, as its core disadvantage results from a lower silhouette coefficient for W only.

All in all, both clustering approaches and both rule-based approaches proved to be capable of recommending diverse partitions to which DMUs fit well, at least. The diversity of the partitions results in a different number of clusters (ranging from 6 in the case of the Pareto rule to 11 in the case of the Szczotka–Spaeth technique) and differences in silhouette coefficient values for individual DMUs. The results of the calculations conducted show that very good partitions – in terms of both average and maximum silhouette coefficients (values over 0.71) – are provided by the corrected results of the application of the VIKOR-like and Pareto rule-based approaches. Note, however, that the results provided by the use of both clustering approaches and the simple gradient approach, in particular, do not prove to be significantly worse in this regard. Moreover, the partitions provided by correcting the direct VIKOR-like rule and using a simple gradient technique are almost the same, with only two DMUs – Z and F – being treated differently by these methods. Note that balanced partitions are ultimately recommended by the application of all four approaches, as the standard deviation level for individual silhouette coefficient values is relatively low. Almost all the approaches proved to be capable of recommending partitions in which more than half of the DMUs form clusters consisting of at least two DMUs Szczotka–Spaeth is, nevertheless, a notable exception in this regard.

5. CONCLUSIONS

Some possible ways to interpret the results of qualitative AHP/ANP technique applications in a more adequate manner were discussed in the paper. The application of both common hierarchical clustering approaches (the simple gradient approach and the Szczotka–Spaeth technique), as well as simplified approaches based on discrimination rules (the Pareto rule and the VIKOR-like rule), is considered in this regard. Two distinct real case studies, which differed in the number of DMUs, were used to initially assess the suitability of the approaches for an adequate analysis of AHP/ANP results.

It turns out that common clustering approaches seem to be generally capable of providing adequate means for expressing qualitative differences between DMUs, thanks to their reliable division among distinct groups, regardless of how many DMUs are actually considered. Their use, particularly the use of a less tedious and simpler gradient approach, is therefore recommended.

The considered simplified rule-based approaches are generally less tedious but do not seem to directly succeed in recommending partitions in which all DMUs fit well, at least. However, the quality of the corrected results from their application, obtained for a considerable number of DMUs, seems to suggest that they may, nevertheless, prove to be useful in peculiar circumstances, at least. This is because they seem to be capable of providing a reliable basis for the identification of unique competitive partitions that common clustering approaches were not aware of at all. Hence, although they do not seem to directly derive reliable DMUs partitions, they should not be disregarded.

It is obvious that the rather limited scope of the conducted analysis does not allow for the formation of reliable general conclusions. Further research is recommended; therefore, a comprehensive investigation into the effects of using considered approaches for grouping AHP/ANP application results is necessary to facilitate their qualitative interpretation. For instance, simulating the influence of the number of DMUs and other parameters of decision analysis problems on the effects of using the approaches could prove advantageous in this regard. The verification of the suitability of other approaches is also welcome. For example, the application of diverse metrics for cluster separation quality assessment (Bezdek & Pal, 1998; Dunn, 1973; Pakhira et al., 2004; Tibshirani et al., 2001) and various clustering techniques (Ismkhan, 2017; Mankowski & Moshkov, 2021; Szkaliczki, 2016; Wang & Song, 2011). The influence of the use of different priority estimation techniques and assessment scales in AHP/ANP, as well as similarity metrics, may also be considered in this regard. All in all, it is nonetheless hoped that the paper will foster a serious discussion about the adequate way to interpret the results provided by AHP/ANP applications in a meaningful and consistent manner, at least.

REFERENCES

Bezdek J.C. & Pal N.R. (1998). Some new indexes of cluster validity. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, **28**(3), pp. 301–315. **DOI:** https://doi.org/10.1109/3477.678624.

Dunn J.C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Journal of Cybernetics,* **3**(3), pp. 32–57. **DOI:** https://doi.org/10.1080/01969727308546046.

Florek K., Łukaszewicz J., Perkal J., Steinhaus H. & Zubrzycki S. (1951). Taksonomia numeryczna wrocławska. *Przegląd Antropologiczny*, **17**, pp. 193–211.

Ginda G. & Szyba M. (2020). How different are Polish regions with regard to the utilisation of biogas plant technology application potential? [In:] *ISAHP 2020 Web conference.* **URL:** https://isahp2020.exordo.com/files/papers/107/final_draft/ggms_isahp2020.pdf [10.12.2020].

Ishizaka A., Nemery P. & Pearman C. (2012). AHPSort: An AHP based method for sorting problems. *International Journal of Production Research*, **50**(17), pp. 4767–4784. **DOI:** https://doi.org/10.1080/00207543.2012.657966.

Ismkhan H. (2017). A.1D-C: A novel fast automatic heuristic to handle large-scale one-dimensional clustering. *Applied Soft Computing*, **52**, pp. 4767–4784. **DOI:** https://doi.org/10.1016/j.asoc.2016.09.001.

Kaufman L. & Rousseeuw P.J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken, NJ: Wiley-Interscience. **DOI:** https://doi.org/10.1002/9780470316801.

Kolenda M. (2006). *Taksonomia numeryczna. Klasyfikacja, porządkowanie i analiza obiektów wielocechowych*. Wrocław: Wydawnictwo Akademii Ekonomicznej im. Oskara Langego.

Mankowski M.A. & Moshkov M.J. (2021). One-dimensional clustering. *Studies in Systems, Decision and Control*, **331**, pp. 123–133.

Netto A.L., Salomon V.A.P., Ortiz-Barros M.A., Florek-Paszkowska A.K., Petrillo A. & De Oliveira O. (2021). Multiple criteria assessment of sustainability programs in the textile industry. *International Transactions in Operational Research*, **28**, pp. 1550–1572. **DOI:** https://doi.org/10.1111/itor.12871.

Opricovic S. (1988). *Multicriteria Optimization of Civil Engineering Systems*. Belgrade: Faculty of Civil Engineering, University of Belgrade.

Opricovic S. & Tzeng G.-H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, **156**(2), pp. 445–455. **DOI:** https://doi.org/10.1016/S0377-2217(03)00020-1.

Pakhira M.K., Bandyopadhyay S. & Maulik U. (2004). Validity index for crisp and fuzzy clusters. *Pattern Recognition* **37**(3), pp. 487–501. **DOI:** https://doi.org/10.1016/j.patcog.2003.06.005.

Saaty T.L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*, New York: McGraw-Hill.

Saaty T.L. (1996). *Decision Making with Dependence and Feedback*. Pittsburgh: RWS.

Spaeth H. (1973). Algorithm of clustering of one-dimensional data ordered data. *Computing*, **11**(2), pp. 175–177. **DOI:** https://doi.org/10.1007/BF02252907.

Szczotka F.A. (1972). On the method of ordering and clustering objects. *Zastosowania Matematyki*, **XIII**(1), pp. 23–34.

Szkaliczki T. (2016). Clustering.sc.dp: Optimal clustering with sequential constraint by using dynamic programming. *R Journal*, **8**(1), pp. 318–327. **DOI:** https://doi.org/10.32614/rj-2016-022.

Tibshirani R., Walter G. & Hastie T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, **63**(2), pp. 411–423. **DOI:** https://doi.org/10.1111/1467-9868.00293.

Wang H. & Song M. (2011). Ckmeans.1d.dp: Optimal k-means clustering in one dimension by dynamic programming. *R Journal* **3**(2), pp. 29–33. **DOI:** https://doi.org/10.32614/RJ-2011-015.

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Operations Research in Municipal Solid Waste Management: Decision-Making Problems, Applications, and Research Gaps

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Abstract. Municipal Solid Waste Management (MSWM) represents a complex, multi-level decision domain that involves strategic, tactical, and operational planning under economic, environmental, and social constraints. This paper reviews the state of Operations Research (OR) applications to MSWM. The analysis encompasses optimization, simulation, metaheuristic, and hybrid approaches that address decision problems ranging from facility siting and capacity expansion to routing and scheduling. The study classifies OR contributions across decision levels, identifying methodological patterns and dominant model types such as mixed-integer programming, metaheuristics, and simulation-optimization frameworks. Despite significant progress in optimization and the integration of sustainability, critical gaps remain in uncertainty modeling, system-wide integration, and data-driven decision support. Deterministic formulations prevail at the strategic and tactical levels, while uncertainty is mainly explored in operational routing. Cross-level coordination among infrastructure planning, fleet design, and daily operations remains underdeveloped. Furthermore, persistent data scarcity and the limited incorporation of behavioral factors constrain the practical applicability of OR models. The review concludes with a research agenda that advocates for multi-level, uncertainty-aware, and dynamic optimization frameworks, supported by standardized data infrastructures and behavioral insights.

Keywords: Municipal Solid Waste Management, Operations Research, optimization, vehicle routing, stochastic modeling, simulation-optimization, multi-objective decision making, sustainability, uncertainty

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1. THE GLOBAL IMPERATIVE FOR OPTIMIZED MUNICIPAL SOLID WASTE MANAGEMENT

Municipal Solid Waste Management (MSWM) has emerged as a significant global challenge, driven by the relentless forces of rapid urbanization, population growth, and shifting consumption patterns. Ineffective MSWM poses severe threats, contributing to public health issues, environmental degradation, and the depletion of natural resources. The scale of this crisis is staggering, with global MSWM production surpassing 2 billion tons annually. Without decisive action, projections suggest this figure could double to approximately 4 billion tons by 2100. This trajectory highlights the pressing need for robust, structured, and strategic-level decision-making frameworks.

The complexity of MSWM extends far beyond a simple technical problem. It is a multi-dimensional system encompassing a wide range of interconnected economic, environmental, and social factors. The entire waste value chain – from generation and collection to treatment and disposal – presents numerous decision points that require sophisticated analysis to ensure sustainability. In this context, decision-making cannot rely on reactive, ad-hoc measures. Instead, it requires a proactive and comprehensive approach that can balance conflicting objectives, such as minimizing costs, reducing environmental footprints, and ensuring social acceptability.

Operations Research (OR) offers a foundational discipline for addressing the intricate decision-making problems inherent in MSWM. By employing mathematical modeling, optimization techniques, and various algorithms, OR provides a powerful toolkit for analyzing complex systems and identifying optimal or near-optimal solutions. Application of OR techniques can lead to significant cost savings and improved waste recovery, making them a crucial component of any modern waste management system (Ghiani et al., 2014). Within this framework, a broad array of OR techniques has been developed to address the diverse decision-making challenges of MSWM, ranging from optimization-based planning to simulation and hybrid methods. Optimization models dominate at the strategic and tactical levels, where Mixed-Integer Programming (MIP) and decomposition techniques have been widely employed for facility location, network design, and multi-objective tradeoffs (Ghiani et al., 2014). Rich MIP formulations also appear in Vehicle Routing Problems (VRPs) for selective waste collection, incorporating facility and material compatibility constraints (Korcyl et al., 2019). Simulation models, both discrete and continuous, have been used to evaluate MSWM system performance and design recycling programs under operational-level variability (Antmann et al., 2013). Metaheuristics and matheuristics represent the state of practice for the Waste Collection and Routing Problems (WCRP), with algorithms such as Ant Colony Optimization (ACO), Simulated Annealing (SA), Genetic Algorithms (GA), Large Neighborhood Search (LNS), Greedy Randomized Adaptive Search Procedures (GRASP), and Adaptive Large Neighborhood Search (ALNS) – often in hybrid configurations (Han & Ponce-Cueto, 2015; Xu et al., 2015). Examples include sectoring-routing local search approaches (Cortinhal et al., 2016) and hybrid ACO-SA models with Taguchi parameter tuning (Tirkolaee et al., 2020). Simulation-optimization frameworks (simheuristics) have emerged to address stochastic travel times and time-dependent routing by embedding Monte Carlo simulation within metaheuristic search (Gruler et al., 2020). Finally, uncertainty modeling remains a challenge: fuzzy chance-constrained formulations have been proposed for demand uncertainty (Tirkolaee et al., 2020), and stochastic travel conditions are commonly handled through simulation (Gruler et al., 2020); yet, comprehensive end-to-end stochastic optimization formulations across decision levels are still limited, as several reviews have noted (Tirkolaee et al., 2018).

The literature provides solid strategic-tactical-operational level framing for MSWM primarily via broad surveys (Asefi et al., 2020; Ghiani et al., 2021) and a deep, globally oriented operational-level routing corpus (Beliën et al., 2014; Han & Ponce-Cueto, 2015), with uncertainty and hybrid sim-opt demonstrated mainly at the operational level (Antmann et al., 2013; Gruler et al., 2020; Tirkolaee et al., 2020), but it lacks an explicit end-to-end, uncertainty-aware, multi-level optimization synthesis with a formal problem-method matrix. Therefore, this work provides a review of the state of OR applications in MSWM, with a specific focus on the body of knowledge published through 2021. The aim is to systematically analyze and synthesize the existing literature, distinguishing between strategic, tactical, and operational decision-making problems in municipal solid waste management through the lens of OR. A central objective is to identify and articulate the key research gaps and limitations that existed in the field at that time, thereby providing a clear agenda for future research. The review focuses on studies that apply optimization, simulation, metaheuristics, or hybrid approaches, particularly those addressing uncertainty in decision-making processes. This analysis not only documents progress but also highlights the critical areas where traditional OR models fall short, thereby paving the way for more integrated and practical solutions. In addition to methodological and hierarchical dimensions, two cross-cutting challenges are increasingly evident in the recent literature: (1) the limited integration of behavioral and social factors influencing waste generation and participation, and (2) persistent data quality and infrastructure constraints that affect the calibration and implementation of OR models. These issues shape the practical feasibility of optimization frameworks and are therefore taken into account when identifying the main research gaps. The review focuses on peer-reviewed studies published between 2000 and 2021, collected primarily through targeted searches in Semantic Scholar, ScienceDirect, Scopus, and Google Scholar. The selection emphasizes works applying optimization, metaheuristics, simulation, or hybrid analytical approaches to municipal solid waste management decision problems. Studies were included if they (1) explicitly formulated the problem using OR techniques and (2) addressed decisions at the strategic, tactical, or operational level. Classic foundational works were retained where they continue to serve as methodological reference points. Publications after 2021 were not systematically reviewed; therefore, emerging topics such as fleet electrification, dynamic and online routing, and IoT-enabled real-time optimization are acknowledged as relevant but fall outside the temporal scope of this study. This clarification ensures the analytical consistency of the review period.

Three research questions guide the investigation:

- RQ1: How have MSWM decision problems been classified and modeled across the strategic, tactical, and operational levels?
- RQ2: Which OR problem classes, methodological families, and uncertainty modeling approaches dominate at each level?
- RQ3: What forms of methodological integration exist across decision levels, and what gaps remain in end-to-end, multi-objective, and uncertainty-aware modeling?

The review does not claim to be exhaustive. Instead, it focuses on representative studies that reflect the dominant modelling approaches and methodological developments in the period examined. The review encompasses peer-reviewed journal articles and full conference papers published in English prior to October 31, 2021. Eligible studies focus on municipal solid waste management systems covering at least one central process stage – generation, collection, transfer, treatment, or disposal – and employ recognized OR methodologies. Optimization models (e.g., MIP, Mixed-Integer Quadratic Programming (MIQP), decomposition), simulation approaches (discrete-event or system dynamics), metaheuristic algorithms, and simulation-optimization hybrids are all eligible for inclusion. Studies must also exhibit methodological generalizability beyond single-city applications or explicitly incorporate uncertainty through stochastic, robust, fuzzy, or chance-constrained formulations.

Papers were excluded if they focused solely on non-municipal waste streams, such as industrial, hazardous, or electronic waste; if they lacked a formal optimization component, such as purely Internet of Things (IoT), Geographic Information System (GIS), or Multiple-Criteria Decision Analysis (MCDA) applications; or if they addressed isolated processes, like waste-to-energy plants or market analyses, without broader system optimization. Algorithmic studies without a substantive connection to MSWM planning were also omitted.

The primary search was conducted using the Semantic Scholar, PubMed, and arXiv databases to cover as many papers as possible, including those not indexed in Scopus or Web of Science. Searches combined waste management and OR terminology using Boolean structures such as: "municipal solid waste" OR "solid waste" AND (optimization OR simulation OR "operations research" OR "stochastic" OR "robust" OR "metaheuristic" OR "chance constrained") AND (strategic OR tactical OR operational OR routing OR siting OR "network design" OR "capacity expansion"). The time window extended from database inception to the end of 2021, and only peer-reviewed English-language publications were retained. Additional material was identified through backward and forward snowballing from established reviews and methodological anchors, such as Beliën et al. (2014), Ghiani et al. (2014), and Asefi et al. (2020).

2. A TAXONOMY OF OPERATIONS RESEARCH APPLICATIONS IN MSWM

This section establishes a structured framework for understanding the field by categorizing OR applications into strategic and tactical decision levels. This taxonomy provides a clear lens for analyzing research gaps. The focus at the strategic level lies in designing long-term system configurations – optimizing facility locations, capacities, waste flows, and technology portfolios under economic, environmental, and policy constraints. Decide the structure and long-term capacity of the system (generation → collection interface → transfer → treatment/recovery → disposal), typically via fixed-charge siting and multi-period expansion choices under multi-objective trade-offs. Surveys covering these decisions and methods include strategic/tactical levels OR in MSWM and integrated MSWM with sustainability framing (Asefi et al., 2020; Ghiani et al., 2014). Tactical level problems in MSWM involve designing medium-term policies and templates that bridge strategic infrastructure and day-to-day operations, including stable service districts, visit calendars/frequencies, fleet mix and shift templates, and assignments to depots/transfer/treatment (Beliën et al., 2014; Cortinhal et al., 2016; Ghiani et al., 2014). At the operational level, decision-making translates strategic and tactical level plans into the daily execution of collection services. This layer involves assigning stops to vehicles and crews, and scheduling trips and also unloads at transfer or treatment facilities, coordinating selective streams, and responding in (near) real time to traffic, equipment failures, or overflow events. It bridges long-term system design with day-to-day logistics, ensuring that municipal solid waste is collected efficiently, safely, and in accordance with service-level agreements (Asefi et al., 2020; Beliën et al., 2014; Ghiani et al., 2014). The taxonomy of representative OR problem areas in MSWM is presented in Table 1.

Table 1. *Representative OR problem areas in Municipal Solid Waste Management*

OR problem area	Corresponding MSWM task	Primary objective(s)	Representative OR models / techniques	Exemplary works
Facility Siting / Location–Allocation	Strategic-level planning of landfills, transfer stations, and treatment facilities	Minimize investment and transport costs; ensure service coverage; reduce environmental impact.	MIP; network design; decomposition approaches	Ghiani et al. (2014); Koushik et al. (2018, 2020)
Districting / Sectorization	Tactical-level partitioning of service areas into compact, contiguous, and balanced sectors	Minimize workload imbalance and travel cost; ensure compactness and contiguity	Multi-objective MIP; local search; matheuristics; GIS-assisted clustering	Billa et al. (2014); Cortinhal et al. (2016); Ghiani et al. (2014); Hemidat et al. (2017); Singh and Behera (2019)
Periodic Routing / Frequency Setting (PVRP)	Tactical-level scheduling of periodic waste collection by zone or waste stream	Minimize service cost and overflow risk; maintain reliability	Multi-period VRP formulations; metaheuristics (GA, ALNS, VNS)	Asefi et al. (2020); Beliën et al. (2014); Tirkolaee et al. (2018)

Table 1 cont.

OR problem area	Corresponding MSWM task	Primary objective(s)	Representative OR models / techniques	Exemplary works
Vehicle Routing (VRP)	Tactical/ operational level design of daily collection routes for vehicle fleets	Minimize total travel time, cost, and emissions while balancing workload	Exact MILP; metaheuristics (GA, SA, GRASP, ACO); hybrid GIS-based solvers	Beliën et al. (2014); Benjamin & Beasley (2010); Nuortio et al. (2006)
Routing with Intermediate Facilities (VRPIF)	Operational-level routing, including unloading trips to transfer/sorting stations	Minimize route time and unloading cost; respect facility windows and capacities	Multi-depot VRP; decomposition; heuristic-MIP hybrids	Benjamin & Beasley (2010); Ghiani et al. (2014)
Selective / Multi-Compartment Collection	Operational-level design of segregated or multi-stream collection	Minimize total distance and contamination; ensure vehicle-stream compatibility	MIP; rich VRP constraints; heuristic search	Goulart Coelho et al. (2017); Tirkolaee et al. (2018)
Fleet Sizing and Composition	Tactical-level determination of fleet size, type, and allocation to depots	Minimize investment and operating cost; match service frequency and workload	MILP; multi-period optimization; cost-based fleet allocation	Ghiani et al. (2014); Koushik et al. (2020); Rabbani et al. (2016);
Integrated Supply Chain / Network Optimization	System-level coordination of collection, transport, treatment, and disposal	Minimize total system cost; improve recycling and resource recovery efficiency	Multi-objective mathematical programming; multi-period flow models	Asefi et al. (2020); Goulart Coelho et al. (2017)
Uncertainty and Robustness in Operations	Operational-level planning under uncertain waste generation and travel times	Improve reliability; minimize overflow and overtime risks	Fuzzy optimization; stochastic programming; simheuristics	Asefi et al. (2020); Beigl et al. (2008); Tirkolaee et al. (2020)
Simulation for Policy and Operational-level Evaluation	Evaluation of new collection policies or recycling programs	Assess service quality, costs, and environmental outcomes	Discrete-event and continuous-discrete simulation frameworks	Antmann et al. (2013); Asefi et al. (2020)

As summarized in Table 1, the body of research demonstrates a clear methodological stratification. Strategic-level models remain dominated by mixed-integer formulations for long-term infrastructure and technology choices. In contrast, tactical-level models increasingly combine multi-objective optimization with matheuristics to balance efficiency, workload, and environmental criteria. Operational-level models, in turn, feature the most mature algorithmic development, especially in rich vehicle routing and scheduling variants. This structure highlights both the progression of methodological sophistication across levels and the persistent gaps in cross-level integration.

2.1. Strategic level problems

Strategic-level decision-making in MSWM is dominated by optimization models that formalize long-term system configuration, facility development, and technology selection as complex mathematical programs. According to Ghiani et al. (2014) and Asefi et al. (2020), these canonical problems can be categorized into several classes, including facility location and capacity sizing, multi-period expansion planning, technology and process-network design, multi-commodity network optimization, and policy-oriented system design. A foundational work by Ghiani et al. (2014) categorized these problems as location-allocation, network design, and system expansion models, which are most frequently formulated as MILP. These formulations typically minimize total system cost – including transportation, operation, and investment – while satisfying service coverage and environmental regulations. Multi-objective extensions balance conflicting goals such as minimizing cost, maximizing recycling, and reducing emissions.

The facility location and capacity sizing problem – deciding where to site landfills, transfer stations, material recovery facilities, composting or anaerobic digestion plants, waste-to-energy units, and residual disposal facilities – is a foundational optimization challenge. It is most often modeled as a fixed-charge facility location or capacitated network design problem solved through MIP or MIQP (Tirkolaee et al., 2018). These formulations minimize total system costs, accounting for capital investment, transportation, and operation, subject to constraints on facility capacity, siting restrictions, and service coverage. Multi-objective variants add diversion rates, greenhouse gas (GHG) emissions, and equity metrics as objectives. Cunha and Caixeta Filho (2002) advanced this line of research through a nonlinear goal programming model that simultaneously optimized economic efficiency, environmental quality, and social acceptability – one of the earliest multi-criteria optimization approaches in MSWM.

Multi-period capacity expansion planning is another critical strategic-level problem, involving decisions on the timing and scale of facility development, landfill cell construction, and technology upgrades in response to growth and regulatory pressures. Tirkolaee et al. (2018) describe these as multi-stage MILP models, featuring binary variables for facility opening and continuous flow variables, which are often solved using decomposition or Lagrangian relaxation to address the large-scale complexity. Similarly, Koushik et al. (2018, 2020) optimized the placement and capacity of treatment, transfer, and disposal facilities over multiple planning periods, demonstrating that the inclusion of transfer stations reduced total costs and transport distances by more than 10%. Their comprehensive MILP framework integrated treatment, transport, and transfer station location to minimize total system cost while ensuring network balance.

The technology selection and process-network design problem focuses on determining the optimal mix of recycling, composting, thermal, and residual disposal technologies. These models, typically formulated as multi-objective MILPs (Asefi et al., 2020; Tirkolaee et al., 2018), incorporate mass-energy balance equations to represent the yields of material and energy recovery. Studies such as those by Aliaga et al. (2021) have extended this approach to reverse logistics network optimization, where recovered materials are reintroduced into secondary markets. In parallel, multi-commodity network design models configure segregated waste streams (residual, recyclables, organics, bulky waste) across a regional network, minimizing costs or environmental impact while respecting contamination thresholds and market constraints (Tirkolaee et al., 2018). Regionalization and contracting models add another layer of realism by optimizing inter-municipal cooperation and shared infrastructure, often through cooperative cost-sharing or bilevel optimization structures.

Optimization at the strategic level also extends to policy design and regulatory planning, optimization models integrating policy instruments – such as pay-as-you-throw schemes, recycling incentives, and landfill taxes – into system-level design. These frameworks often use bi-level or scenario-based optimization to simulate the effects of policy on infrastructure investment and waste flows. At the same time, Asefi et al. (2020) emphasize the integration of energy and by-product recovery into planning models, coupling waste networks with power or heat grids to account for emission-revenue trade-offs. The complementary analyses by Goulart Coelho et al. (2017) highlight the use of multi-objective and game-theoretic formulations to examine the interactions among policy incentives, technology selection, and economic outcomes.

Across these classes, optimization objectives typically include minimizing total life-cycle cost, maximizing diversion or resource recovery rates, and minimizing GHG or pollutant emissions – often addressed through the ε-constraint or Pareto-front methods (Tirkolaee et al., 2018). Typical constraints capture facility and transport capacities, regulatory and environmental limits, contamination and quality specifications, labor availability, and spatial equity (e.g., maximum service distance). To handle uncertainty in waste generation, participation, material yields, energy prices, and regulation, models employ two-stage and multi-stage stochastic programming, robust optimization, and chance-constrained formulations, supplemented by simulation-based evaluations where analytical modeling is infeasible (Tirkolaee et al., 2018).

Empirical evidence further demonstrates the practical application of these optimization frameworks in real-world settings. Cabrera and Yabar (2018) developed a network-based spatial analysis framework for locating waste recovery facilities in Concepción, Chile, optimizing accessibility and transport efficiency through GIS-based network modeling. This finding underscores the trade-offs inherent in multi-objective optimization. Nevertheless, as Zeiss and Lefsrud (1996) and Vári (2000) emphasize, technically optimal solutions can face public opposition and governance barriers, revealing a persistent gap between mathematical optimality and social feasibility.

Strategic-level optimization in MSWM is grounded in MIP-based models for fixed-charge location, capacity expansion, and multi-objective network design, often supplemented by decomposition and stochastic extensions. These formulations have proven effective for system-level planning, technology selection, and policy evaluation. However, as Asefi et al. (2020) note, key gaps remain in incorporating uncertainty, dynamic capacity expansion, behavioral factors, and intertemporal policy feedback. Addressing these gaps through integrated, stochastic, and participatory optimization frameworks represents a crucial direction for future research in sustainable waste management planning.

2.2. Tactical level problems

At the tactical level of decision-making, OR provides analytical support for medium-term planning decisions that link long-term infrastructure design with short-term operational control. These optimization models address collection sectorization, routing, frequency planning, fleet allocation, and transfer network coordination, all of which are subject to resource, regulatory, and spatial constraints. This layer bridges strategic-level planning and daily operations, defining how available resources are organized to ensure continuous and efficient service delivery. As noted by Beliën et al. (2014), and Ghiani et al. (2014) tactical-level optimization in MSWM determines the configuration of collection districts, service frequencies, fleet composition, and depot assignments while balancing economic efficiency, environmental performance, and workload distribution.

A foundational tactical-level problem is districting or sectorization, in which municipalities are divided into compact, contiguous service zones that balance workloads among collection crews. Cortinhal et al. (2016) developed a sectoring-routing heuristic that jointly optimizes district boundaries and route design to achieve compactness and workload equity. Similarly, Kallel et al. (2016) integrated GIS tools into sectoring and routing optimization, demonstrating how geospatial data supports balanced and feasible collection plans. Huang and Lin (2015) extended this framework by incorporating social and policy constraints such as street access and collection time restrictions, demonstrating how tactical-level planning can reflect local regulations. Araiza-Aguilar et al. (2021) and Majid et al. (2021) proposed one of the early GIS-assisted heuristic approaches that incorporated vehicle accessibility into districting design, illustrating the role of spatial modeling in enhancing real-world feasibility. According to Ghiani et al. (2014), such problems are typically formulated as multi-objective MIP problems or solved with matheuristics, where cost minimization, travel-time balance, and compactness compete as key objectives. Reviews by Beliën et al. (2014) confirm that decomposition and local search techniques dominate this field due to the high combinatorial complexity of maintaining contiguity and balance constraints.

Tactical-level models also cover container allocation and vehicle coordination, which link strategic-level siting with operational-level routing. Mahéo et al. (2020) proposed a Benders decomposition model that integrates bin placement with route optimization, bridging long-term infrastructure design with tactical-level service planning. Likewise, Aliahmadi et al. (2020) introduced a fuzzy optimization approach for capacitated node-routing problems with multiple tours, embedding uncertainty in waste volumes – a rare example of explicit tactical-level uncertainty modeling. Container placement and sizing models, reviewed by Asefi et al. (2020) and Ghiani et al. (2014), determine the optimal number, type, and location of bins using integer programming, subject to accessibility constraints, contamination thresholds, and vehicle-container compatibility. These problems form a closed tactical-level decision loop that directly interacts with routing and frequency-setting tasks. In selective or segregated collection systems, additional complexity arises from waste-stream compatibility: Tirkolaee et al. (2018) and Goulart Coelho et al. (2017) modeled multi-commodity vehicle routing with compatibility matrices that account for multi-compartment vehicles and differentiated waste flows.

A related and long-studied tactical-level problem is periodic collection and frequency setting, often formalized as the Periodic Vehicle Routing Problem (PVRP). Beliën et al. (2014) and Asefi et al. (2020) describe how these formulations determine optimal day-of-week or seasonal schedules to minimize overflow risk while maintaining service reliability. Such models capture both routing and scheduling decisions and are frequently solved using metaheuristics – notably GA, Adaptive Large Neighborhood Search (ALNS), and Variable Neighborhood Search (VNS). Tirkolaee et al. (2018) extended the PVRP framework to multi-period and multi-objective MIPs, including environmental and capacity constraints, while Lei et al. (2020) introduced a discrete-continuous hybrid approach for recycling collection that captures tactical-level trade-offs between service intervals and processing coordination. Delgado-Antequera et al. (2020) and López-Sánchez et al. (2018) further developed multi-objective models, solved using GRASP-Variable Neighborhood Descent (VND) algorithm and iterated greedy heuristics, that simultaneously optimize cost, workload balance, and emissions.

The allocation of service zones to depots and transfer stations represents another canonical tactical-level issue. As Ghiani et al. (2014) note, this can be expressed as a Multi-Depot Vehicle Routing Problem (MDVRP) in which subareas are assigned to facilities subject to capacity, haul distance, and time-window constraints. Koushik et al. (2018, 2020) extended this logic in integrated MILP frameworks that combine depot assignment, fleet sizing, and transfer station utilization, demonstrating that optimized depot allocation can reduce system costs and travel distances by over 10%.

Tactical-level OR has also addressed heterogeneous fleet allocation and multi-compartment vehicle routing, especially under selective collection regimes. Rabbani et al. (2016) developed a hybrid GA to optimize heterogeneous fleet routing with multiple compartments for recyclable and residual waste. Assaf and Saleh (2017) employed GA-based optimization to adapt fleet routes to terrain and access limitations, whereas Das and Bhattacharyya (2015) calibrated deterministic fleet-route models for Indian cities to minimize collection and transfer costs. These works collectively demonstrate the diversity of tactical fleet planning approaches.

The literature also documents growing attention to multi-objective and stochastic tactical-level planning. Marković et al. (2019) and Tirkolaee et al. (2020) incorporated stochastic demand and fuzzy travel times into routing formulations. In contrast, Asefi et al. (2020) reviewed hybrid frameworks that combine MIP formulations with simulation or metaheuristics to manage uncertainty. Delgado-Antequera et al. (2020) introduced bi-objective optimization for cost-equity trade-offs, and Ghiani et al. (2014) emphasized workload balance as a key equity-based constraint.

Recent research trends have led to a shift in tactical-level models toward integrated and sustainability-oriented planning. Koushik et al. (2018) and Lei et al. 2020) incorporated recycling, energy recovery, and emissions into multi-objective frameworks, transforming traditional cost-based optimization into sustainability-driven decision-making. Similarly, Mojtahedi et al. (2021) and Asefi et al. (2020) linked routing and fleet planning with smart-city infrastructures, reflecting the increasing digitalization of tactical management.

Typical objectives of tactical-level models include minimizing total service cost (vehicle-hours, distance, fuel use), balancing crew workloads, and reducing environmental externalities such as emissions and noise (Beliën et al., 2014; Cortinhal et al., 2016; Ghiani et al., 2014). Typical constraints address compactness, service coverage, vehicle-waste compatibility, working hours, and depot capacities. Multi-objective trade-offs are frequently handled using ε-constraint or weighted-sum approaches (Tirkolaee et al., 2018). Simulation – especially with discrete-event and hybrid continuous-discrete models – is often used to test proposed collection policies and recycling initiatives before implementation (Antmann et al., 2013; Asefi et al., 2020).

Despite this methodological progress, the treatment of uncertainty remains a persistent gap at the tactical level. While operational-level studies frequently employ fuzzy and stochastic formulations, few works have applied these methods to tactical-scale models (Asefi et al., 2020; Tirkolaee et al., 2020). Beigl et al. (2008) emphasized that forecast uncertainty in waste generation and participation rates can substantially affect tactical-level planning, yet most studies continue to assume deterministic inputs.

Literature published between 2000 and 2021 reveals a clear evolution from deterministic routing and fleet sizing toward multi-objective, uncertain, and integrated tactical-level planning that accounts for environmental and operational variability. Nevertheless, as Ghiani et al. (2014) and Asefi et al. (2020) emphasize, the full integration of uncertainty and cross-level coupling across the tactical, strategic, and operational layers remains underdeveloped. Addressing these gaps requires end-to-end stochastic optimization frameworks that integrate tactical-level decisions on routing, sectorization, and fleet renewal with long-term sustainability and policy objectives.

2.3. Operational level problems

At the operational level, decision-making transforms strategic and tactical level plans into daily waste collection activities, enabling the design of efficient, reliable, and cost-effective services. This stage includes assigning stops to vehicles and crews, scheduling trips and unloads at transfer facilities, coordinating selective streams, and responding to traffic conditions or container overflow (Asefi et al., 2020; Beliën et al., 2014; Ghiani et al., 2014).

The VRP and its variants are the dominant operational-level formulations in the waste management literature. Foundational contributions, such as those by

Nuortio et al. (2006) and Benjamin & Beasley (2010), applied metaheuristics, including genetic algorithms, simulated annealing, and adaptive large neighborhood searches, to optimize collection routes for heterogeneous fleets and multiple depots. These models were later extended into rich VRPs that incorporate multiple trips, intermediate unloading at transfer stations, and working time limits (Beliën et al., 2014; Ghiani et al., 2014). In practice, these formulations capture the complex interplay between route duration, facility accessibility, and vehicle capacity.

Operational-level problems with intermediate unloading are modeled as the Vehicle Routing Problems with Intermediate Facilities (VRPIF). These formulations schedule unloading trips at transfer or treatment facilities within the daily tour, synchronizing route timing with facility hours and vehicle capacity resets (Benjamin & Beasley, 2010; Ghiani et al., 2014). For selective or multi-compartment collection, where multiple waste streams are collected concurrently, integer programming is used to encode compatibility rules between waste types, compartments, and facilities (Goulart Coelho et al., 2017; Koushik et al., 2018; Rabbani et al., 2016). These models improve route efficiency and compliance with separation requirements while minimizing total distance and operating time.

In arc-routing models, where waste is collected along street segments, capacity and uncertainty are jointly addressed. Tirkolaee et al. (2018) developed a robust periodic capacitated arc routing problem incorporating driver working hours and stochastic demand. Their hybrid ant colony optimization and simulated annealing approach demonstrated that metaheuristics can effectively handle large, uncertain networks, which are typical of municipal collection systems. Similar formulations have been used to balance workload, fuel use, and emissions under constrained shift durations (Tirkolaee et al. 2018, 2020).

Containerized and underground systems have introduced inventory-routing logic into operational-level planning. In such cases, route optimization depends on predicted container fill levels and overflow risk, which are often addressed through heuristics and short-term forecasting (Beliën et al., 2014; Faccio et al., 2011). Other models focus on appointment-based bulky waste collection, typically expressed as VRP with Time Windows variants with heterogeneous service and buffer times to account for schedule uncertainty (Ghiani et al., 2014). Crew assignment and shift feasibility are modeled as resource constraints within routing formulations to ensure compliance with labor and safety regulations (Benjamin & Beasley, 2010; Cortinhal et al., 2016).

Operational-level models typically pursue multi-objective optimization, aiming to minimize service costs and fuel consumption while balancing workload and reducing environmental externalities (Cortinhal et al., 2016; Ghiani et al., 2014). Constraints capture vehicle capacities, time windows, unloading cycles, stream compatibility, and accessibility restrictions (Beliën et al., 2014; Rabbani et al., 2016). Exact MIP is typically feasible only for structured cases, while city-scale problems rely on metaheuristics such as ALNS, GA, GRASP, ACO, and VNS (Benjamin & Beasley, 2010; Tirkolaee et al., 2018).

Simulation methods are increasingly used to evaluate operational policies before they are implemented. Antmann et al. (2013) employed continuous-discrete simulation to test daily and weekly plans, while Johansson (2006) and Ramdhani et al. (2018)

demonstrated real-time rescheduling of waste collection vehicles based on traffic updates. Such models provide insights into system reliability and capacity utilization, complementing optimization-based planning.

Digital and data-driven operations have emerged as a bridge between classical OR and real-time decision-making. Faccio et al. (2011) proposed a multi-objective model that integrates real-time traceability data into routing decisions, while Billa et al. (2014), Hemidat et al. (2017), and Singh & Behera (2019) demonstrated the use of GIS-based optimization for routing under urban accessibility constraints. As reviewed by Asefi et al. (2020), most digital applications framed sensor-driven collection as dynamic VRP or Inventory-Routing Problems, with optimization embedded within feedback control or simulation loops. VRP-based optimization, metaheuristic solution strategies, and increasing integration of simulation and digital monitoring characterize operational-level decision-making in MSWM. Despite this progress, treatment of uncertainty remains limited, and links to tactical and strategic layers are often unidirectional. As noted by Ghiani et al. (2014) and Asefi et al. (2020), future research should focus on fully integrated, stochastic optimization frameworks that connect operational-level responsiveness with long-term system sustainability.

3. RESEARCH GAPS IN THE APPLICATION OF OPERATIONS RESEARCH TO MSWM

Despite significant methodological progress, the literature on OR tools for MSWM remains fragmented across decision levels and constrained in its treatment of uncertainty, sustainability, and data integration. Existing reviews emphasize that although many models address strategic, tactical, or operational level issues individually, few provide an integrated, system-wide perspective that links facility planning, sector design, and daily routing (Asefi et al., 2020; Ghiani et al., 2014; Goulart Coelho et al., 2017). Most formulations continue to rely on deterministic assumptions and static planning horizons, with limited capacity to represent the dynamic and uncertain behavior of real waste systems. As a result, system-level coordination among infrastructure siting, collection frequency, and routing remains a central research gap.

At the strategic level, optimization models typically focus on facility location, capacity, and technology mix, often formulated as MILP (Asefi et al., 2020; Ghiani et al., 2014). While these models capture cost and regulatory constraints, they rarely include explicit feedback from downstream routing and service performance. The decoupling between strategic and operational layers leads to cost estimates that do not fully account for transportation variability, congestion, or selective collection requirements. Few works integrate facility siting and technology selection with realistic routing submodels or stochastic demand conditions (Koushik et al. 2018, 2020). This indicates a methodological opportunity for multi-stage or decomposition-based models that link siting and capacity expansion with collection logistics under uncertainty.

At the tactical level, the literature highlights a dominance of deterministic formulations for districting, service frequency planning, and fleet allocation (Asefi et al., 2020; Beliën et al., 2014; Cortinhal et al., 2016). Although empirical evidence suggests that fluctuations in waste generation and participation impact service quality (Beigl et al., 2008), explicit stochastic or robust tactical-level models remain relatively uncommon. Chance-constrained or fuzzy optimization – frequently applied at the operational level in routing – has seldom been extended to tactical-level problems, such as sectorization or periodic service planning. This gap limits the adaptability of medium-term decisions to real-world demand and travel-time variability.

OR in MSWM has been dominated by routing optimization, especially VRPs and their extensions for time windows, multi-trips, or multiple depots (Benjamin & Beasley, 2010; Nuortio et al., 2006; Tirkolaee et al., 2018, 2020). However, even within this rich corpus, most studies focus on deterministic instances, while only a few consider stochastic travel times or uncertain waste quantities. Simheuristic approaches and fuzzy formulations were introduced to capture these effects (Tirkolaee et al., 2020). However, large-scale applications integrating stochastic routing with upstream tactical or strategic level modules were still absent before 2021. Queueing and synchronization at transfer facilities were generally simplified, despite their importance for operational feasibility (Ghiani et al., 2014).

A recurring challenge across levels is the limited integration of sustainability and equity objectives. Multi-objective models are well established, yet most remain focused on economic and environmental trade-offs, with few incorporating social or fairness constraints (Asefi et al., 2020; Goulart Coelho et al., 2017). Workload balance is reflected in routing formulations (Cortinhal et al., 2016), but explicit environmental justice considerations – such as equitable access to services or reduction of exposure – are rarely formalized. Moreover, uncertainty is rarely considered in sustainability-oriented optimization, thereby reducing the robustness of long-term planning outcomes.

Another structural limitation concerns the reliance on static and scenario-based optimization. Multi-period frameworks exist, but they remain discrete and non-adaptive Digital and IoT-based approaches – such as GIS-assisted routing and fill-level monitoring – have shown potential for dynamic planning (Billa et al., 2014; Faccio et al., 2011; Hemidat et al., 2017; Johansson, 2006; Karadimas & Loumos, 2008; Ramdhani et al., 2018; Singh & Behera, 2019), yet hitherto implementations were largely prototype-scale. Most systems lacked the data infrastructure and standardization required for real-time re-optimization, reflecting a gap between methodological capability and technological readiness.

A foundational obstacle underpinning these issues are data bottlenecks. As Beigl et al. (2008) observed, waste composition and generation rates vary significantly across regions, which limits the transferability of models and the comparability of analysis. Data scarcity also hinders the development of standardized stochastic benchmarks for routing and facility planning. While deterministic routing benchmarks are well established (Benjamin & Beasley, 2010; Nuortio et al., 2006), open datasets incorporating time-dependent speeds, uncertain setups, or facility constraints are still lacking. Without such benchmarks, assessing the performance of stochastic and simulation-based optimization approaches remains challenging.

Critical thematic gaps persist in linking OR models to emerging challenges and transitions. Studies rarely integrate waste quality and market volatility into tactical or strategic level optimization, despite their significant impact on system costs (Goulart Coelho et al., 2017; Koushik et al., 2018). Similarly, hitherto, research has provided little insight into fleet electrification or resilience to shocks such as pandemics or extreme weather events, although these factors are increasingly shaping municipal logistics (Asefi et al., 2020; Tirkolaee et al., 2020). Operational disruptions and dynamic rerouting were discussed conceptually but seldom modeled quantitatively within integrated frameworks (see Table 2).

Table 2. *Identified research gaps and future directions*

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Global pandemic and shock resilience	Lack of comprehensive OR frameworks for managing extreme events that disrupt waste generation, composition, and logistics (e.g., COVID-19)	Asefi et al. (2020); Tirkolaee et al. (2020)	Develop adaptable, resilient optimization models capable of handling sudden changes in waste streams, medical waste surges, and service interruptions through multi-stage and robust formulations
Behavioral integration deficit	Limited modeling of human attitudes, participation rates, and community behavior in optimization; socio-behavioral dimensions treated qualitatively, not mathematically	Beigl et al. (2008); Ghiani et al. (2014)	Combine OR with behavioral modeling by embedding empirical participation data or behavioral response functions into tactical and strategic-level optimization frameworks
Data-driven bottleneck	The persistent lack of standardized, high-resolution, and reliable data on waste generation and composition hinders the transferability and validation of models	Asefi et al. (2020); Beigl et al. (2008)	Develop standardized data collection protocols, interoperable databases, and cost-effective sensor networks; integrate ML-based forecasting into OR models to close the data-model gap
Static vs. dynamic optimization	Over-reliance on static, scenario-based optimization that cannot adapt to real-time fluctuations in waste generation and traffic conditions	Faccio et al. (2011) Ghiani et al. (2014); Johansson (2006); Ramdhani et al. (2018)	Advance dynamic, IoT-enabled optimization and simheuristic models for adaptive routing, load balancing, and overflow prevention under uncertainty

Table 2 cont.

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Lack of integrated system-wide models	Strategic, tactical, and operational-level decisions are modeled separately, resulting in inconsistent system-level solutions	Asefi et al. (2020); Beliën et al. (2014); Ghiani et al. (2014).	Formulate hierarchical or decomposed models that link siting, capacity, and technology mix with districting, fleet planning, and routing using stochastic or multi-stage optimization
Limited uncertainty and robustness treatment	Deterministic assumptions predominate in tactical and strategic-level models, despite the known variability in waste generation and travel times	Beigl et al. (2008); Tirkolaee et al. (2018, 2020)	Extend robust and stochastic programming approaches to tactical and multi-period planning, applying chance constraints to optimize overflow and service reliability
Weak sustainability and equity integration	Environmental and social dimensions are often reported post-hoc rather than embedded in optimization objectives or constraints	Asefi et al. (2020); Ghiani et al. (2014); Goulart Coelho et al. (2017)	Develop multi-objective models explicitly co-optimizing cost, GHG emissions, and service equity using Pareto or ε-constraint methods under uncertainty
Simplified facility and queue representation	Intermediate facility capacities, congestion, and synchronization effects are seldom modeled, biasing routing feasibility and cost estimation	Benjamin & Beasley (2010); Ghiani et al. (2014)	Integrate queueing or simulation components within VRP with intermediate facilities (VRPIF) to capture stochastic unloading and facility interactions
Limited coupling between collection and processing	Models treat collection and treatment as independent subsystems, ignoring contamination, recovery yields, and market volatility	Goulart Coelho et al. (2017); Koushik et al. (2018, 2020)	Develop multi-commodity network models linking collection strategies to processing performance and economic value under uncertain market conditions
Fleet transition and decarbonization gaps	Few studies address the integration of electrification or alternative-fuel fleet routing into infrastructure planning	Asefi et al. (2020); Ghiani et al. (2014)	Extend vehicle-routing models to incorporate charging/refueling constraints, as well as the co-optimization of depot siting, emission reduction, and operational efficiency

Table 2 cont.

Research gap	Substantive issue	Supporting evidence	Proposed future research direction
Limited use of simulation-optimization beyond operations	Simulation is primarily used to evaluate routing performance rather than to optimize decisions at higher levels of abstraction	Asefi et al. (2020); Ghiani et al. (2014)	Combine discrete-event or system dynamics simulation with optimization to evaluate policy and planning alternatives under uncertainty
Absence of standardized benchmarks and open data for stochastic models	Existing benchmark sets cover only deterministic routing; no open datasets for uncertain generation or time-dependent networks	Ghiani et al. (2014); Nuortio et al. (2006)	Establish open, stochastic benchmark datasets and uncertainty scenarios to facilitate comparison and reproducibility of OR methods in MSWM

The state of research reveals several persistent limitations. OR applications in MSWM remain largely fragmented by decision level, constrained by deterministic assumptions, and weakly coupled to sustainability and social objectives. The field still lacks end-to-end stochastic and robust optimization frameworks that bridge infrastructure planning, service design, and routing operations under uncertainty. Progress toward real-time, data-driven decision support was evident but incomplete, constrained by the availability and standardization of waste data. Addressing these gaps – through integrated, uncertainty-aware, and sustainability-oriented modeling – represents a clear direction for future OR research in municipal waste management.

4. CONCLUSION

This review set out to identify and articulate the principal research gaps and limitations in the application of OR to MSWM as of 2021. Guided by three research questions, the analysis has provided a structured understanding of how decision problems have been modeled, which methodological families have dominated, and where the integration of uncertainty, sustainability, and multi-level decision-making remains incomplete.

Addressing RQ1, the classification of MSWM decision problems reveals that OR methods have been extensively applied across all three planning horizons – strategic, tactical, and operational levels. Strategic-level studies have focused primarily on facility siting, capacity expansion, and technology mix decisions, typically formulated as mixed-integer programming models. Tactical-level models have addressed routing, sectorization, fleet composition, and collection frequency, while OR has concentrated on rich vehicle routing problems and daily scheduling under detailed logistical constraints. Over time, the field has evolved from simple, cost-oriented formulations to multi-objective, sustainability-aware models that integrate environmental and service-related performance indicators.

In response to RQ2, the literature emphasizes optimization and metaheuristics, with limited but growing contributions from simulation and hybrid simulation-

-optimization frameworks. While deterministic formulations remain prevalent, stochastic, fuzzy, and robust optimization approaches have been increasingly employed to capture uncertainty in waste generation, participation rates, and travel conditions. However, uncertainty treatment remains mainly confined to operational-level models, leaving higher-level decisions – such as network design and fleet planning – dominated by static and scenario-based approaches. The field's progress in methodological diversity is thus substantial but uneven across decision layers.

Concerning RQ3, methodological integration across decision levels remains an important but underdeveloped frontier. Although several studies recognize the interdependence among strategic, tactical, and operational-level planning, few offer comprehensive frameworks that link facility location, sectoring, and routing decisions under shared stochastic conditions. Most existing models operate in isolation, which limits their ability to represent real-world system interactions and dynamic feedback accurately. Similarly, multi-objective integration – balancing cost, emissions, and equity – has advanced conceptually but is rarely implemented in unified, uncertainty-aware formulations.

Despite these advances, three cross-cutting limitations continue to constrain the field. First, the behavioral integration deficit remains a fundamental barrier. The human and social dimensions of waste generation and participation – despite being acknowledged as critical – have yet to be formally embedded within quantitative OR models. Second, the data-driven bottleneck persists: the lack of standardized, high-quality datasets hinders both model calibration and the adoption of AI- and ML-based predictive approaches. Finally, the transition from static to dynamic optimization represents a significant, yet unfulfilled, opportunity. While IoT technologies promise real-time monitoring and adaptive decision-making, implementation remains limited by infrastructure and cost barriers.

In light of the three guiding research questions, the review reveals that, although strategic, tactical, and operational decision-making problems in MSWM have been widely studied, the corresponding OR models remain methodologically fragmented across these levels. Deterministic formulations continue to dominate, and uncertainty, sustainability criteria, and cross-level integration are addressed unevenly. The review period up to 2021 also reveals growing interest in simulation-based evaluation, yet real-time adaptive optimization remains limited by data availability and interoperability across systems. Future work should therefore prioritize (1) integrated, multilevel decision frameworks, (2) explicit modeling of uncertainty and resilience, and (3) data-driven, dynamically updating optimization supported by sensor and digital monitoring systems. Such developments would enable OR methods to support practical, scalable, and sustainability-aligned MSWM planning and operations more fully.

REFERENCES

Aliaga S., Pradenas L. & Contreras-Bolton C. (2021). A reverse logistics network for recycling in Chile: a case in Concepción. In: *Proceedings of the International Conference on Industrial Engineering and Operations Management*. IEOM Society International, Michigan, USA, pp. 2760–2769.

Aliahmadi S.Z., Barzinpour F. & Pishvaee M.S. (2020). A fuzzy optimization approach to the capacitated node-routing problem for municipal solid waste collection with multiple tours: A case study. *Waste Management and Research: The Journal for a Sustainable Circular Economy*, **38**(3), pp. 279–290. **DOI:** https://doi.org/10.1177/0734242X19879754.

Antmann E.D., Shi X., Celik N. & Dai Y. (2013). Continuous-discrete simulation-based decision-making framework for solid waste management and recycling programs. *Computers & Industrial Engineering*, **65**(3), pp. 438–454. **DOI:** https://doi.org/10.1016/j.cie.2013.03.010.

Araiza-Aguilar J.A., Cram-Heydrich S., Ruiz-Rivera N., Oropeza-Orozco O., del Pilar Fernández Lomelín M. & Neftalí Rojas-Valencia M. (2021). GIS-based approach to zoning the risk associated with municipal solid waste management: Application to regional scale. *Environmental Monitoring and Assessment*, **193**, 69. **DOI:** https://doi.org/10.1007/s10661-021-08864-y.

Asefi H., Shahparvari S. & Chhetri P. (2020). Advances in sustainable integrated solid waste management systems: Lessons learned over the decade 2007–2018. *Journal of Environmental Planning and Management*, **63**(13), pp. 1753–1775. **DOI:** https://doi.org/10.1080/09640568.2020.1714562.

Assaf R. & Saleh Y. (2017). Vehicle-routing optimization for municipal solid waste collection using genetic algorithm: The case of Southern Nablus City. *Civil and Environmental Engineering Reports*, **26**(3), pp. 43–57. **DOI:** https://doi.org/10.1515/ceer-2017-0034.

Beigl P., Lebersorger S. & Salhofer S. (2008). Modelling municipal solid waste generation: A review. *Waste Management*, **28**(1), pp. 200–214. **DOI:** https://doi.org/10.1016/j.wasman.2006.12.011.

Beliën J., De Boeck L. & Van Ackere J. (2014). Municipal solid waste collection and management problems: A literature review. *Transportation Science*, **48**(1), pp. 78–102. **DOI:** https://doi.org/10.1287/trsc.1120.0448.

Benjamin A.M. & Beasley J.E. (2010). Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities. *Computers & Operations Research*, **37**(12), pp. 2270–2280. **DOI:** https://doi.org/10.1016/j.cor.2010.03.019.

Billa L., Pradhan B. & Yakuup A. (2014). GIS routing and modelling of residential waste collection for operational management and cost optimization. *Pertanika Journal of Science and Technology*, **22**(1), pp. 193–211.

Cabrera A.R. & Yabar H. (2018). Solving location allocation problem of waste recovery facilities through the use of network-based spatial analysis. *International Journal of Waste Resources*, **8**, pp. 31. **URL:** https://www.walshmedicalmedia.com/conference-abstracts-files/2252-5211-C2-015-002.pdf [5.10.2021].

Cortinhal M.J., Mourão M.C. & Nunes A.C. (2016). Local search heuristics for sectoring – routing in a household waste collection context. *European Journal of Operational Research*, **255**(1), pp. 68–79. **DOI:** https://doi.org/10.1016/j.ejor.2016.04.013.

Cunha V. & Caixeta Filho J.V. (2002). Gerenciamento da coleta de resíduos sólidos urbanos: Estruturação e aplicação de modelo não-linear de programação por metas. *Gestão & Produção*, **9**(2), pp. 143–161. **DOI:** https://doi.org/10.1590/S0104-530X2002000200004.

Das S. & Bhattacharyya B.K. (2015). Optimization of municipal solid waste collection and transportation routes. *Waste Management*, **43**, pp. 9–18. **DOI:** https://doi.org/10.1016/j.wasman.2015.06.033.

Delgado-Antequera L., Caballero R., Sánchez-Oro J., Colmenar J.M. & Martí R. (2020). Iterated greedy with variable neighborhood search for a multiobjective waste collection problem. *Expert Systems with Applications*, **145**, 113101. **DOI:** https://doi.org/10.1016/j.eswa.2019.113101.

Faccio M., Persona A. & Zanin G. (2011). Waste collection multi-objective model with real-time traceability data. *Waste Management*, **31**(12), pp. 2391–2405. **DOI:** https://doi.org/10.1016/j.wasman.2011.07.005.

Ghiani G., Laganà D., Manni E., Musmanno R. & Vigo D. (2014). Operations research in solid waste management: A survey of strategic and tactical issues. *Computers & Operations Research*, **44**, pp. 22–32. **DOI:** https://doi.org/10.1016/j.cor.2013.10.006.

Ghiani G., Manni A., Manni E. & Moretto V. (2021). Optimizing a waste collection system with solid waste transfer stations. *Computers & Industrial Engineering*, **161**, 107618. **DOI:** https://doi.org/10.1016/j.cie.2021.107618.

Goulart Coelho L.M., Lange L.C. & Coelho H.M.G. (2017). Multi-criteria decision making to support waste management: A critical review of current practices and methods. *Waste Management and Research*, **35**(1), pp. 3–28. **DOI:** https://doi.org/10.1177/0734242X16664024.

Gruler A., Pérez-Navarro A., Calvet L. & Juan A.A. (2020). A simheuristic algorithm for time-dependent waste collection management with stochastic travel times. *SORT: Statistics and Operations Research Transactions*, **44**(2), pp. 285–310. **DOI:** https://doi.org/10.2436/20.8080.02.103.

Johansson O.M. (2006). The effect of dynamic scheduling and routing in a solid waste management system. *Waste Management*, **26**(8), pp. 875–885. **DOI:** https://doi.org/10.1016/j.wasman.2005.09.004.

Han H. & Ponce-Cueto E. (2015). Waste collection vehicle routing problem: Literature review. *Promet – Traffic & Transportation*, **27**(4), pp. 345–358. **URL:** https://scispace.com/pdf/waste-collection-vehicle-r-outing-problem-literature-review-3p4cy8hk2w.pdf [5.10.2021].

Hemidat S., Oelgemöller D., Nassour A. & Nelles M. (2017). Evaluation of key indicators of waste collection using GIS techniques as a planning and control tool for route optimization. *Waste and Biomass Valorization*, **8**, pp. 1533–1554. **DOI:** https://doi.org/10.1007/s12649-017-9938-5.

Huang S.-H. & Lin P.-C. (2015). Vehicle routing – scheduling for municipal waste collection system under the "Keep Trash off the Ground" policy. *Omega*, **55**, pp. 24–37. **DOI:** https://doi.org/10.1016/j.omega.2015.02.004.

Kallel A., Serbaji M.M. & Zairi M. (2016). Using GIS-based tools for the optimization of solid waste collection and transport: Case study of Sfax City, Tunisia. *Journal of Engineering*, 4596849. **DOI:** https://doi.org/10.1155/2016/4596849.

Karadimas N.V. & Loumos V.G. (2008). GIS-based modelling for the estimation of municipal solid waste generation and collection. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, **26**(4), pp. 337–346. **DOI:** https://doi.org/10.1177/0734242X07081484.

Korcyl A., Gdowska K. & Książek R. (2019). A MILP model for the selective solid waste collection routing problem. *Decision Making in Manufacturing and Services*, **13**(1–2), pp. 17–35. **DOI:** https://doi.org/10.7494/dmms.2019.13.1-2.3470.

Koushik P., Subhasish C., Dutta A., Krishna A.P. & Ray S. (2018). A comprehensive optimization model for an integrated solid waste management system: A case study. *Environmental Engineering Research*, **24**(2), pp. 220–237. **DOI:** https://doi.org/10.4491/eer.2018.132.

Koushik P., Chattopadhyay S., Dutta A. Krishna A.P. & Ray S. (2020). Developing and optimising an urban integrated solid waste management model: Effect of transfer stations. *Journal of Urban and Environmental Engineering*, **14**(1), pp. 119–131. **DOI:** https://doi.org/10.4090/juee.2020.v14n1.119131.

Lei C., Jiang Z. & Ouyang Y. (2020). A discrete-continuous hybrid approach to periodic routing of waste collection vehicles with recycling operations. *IEEE Transactions on Intelligent Transportation Systems*, **21**(12), pp. 5236–5245. **DOI:** https://doi.org/10.1109/TITS.2019.2951571.

López-Sánchez A.D., Hernández-Díaz A.G., Gortázar F. & Hinojosa M.A. (2018). A multiobjective GRASP-VND algorithm to solve the waste collection problem. *International Transactions in Operational Research*, **25**(2), pp. 545–567. **DOI:** https://doi.org/10.1111/itor.12452.

Mahéo A., Rossit D.G. & Kilby P. (2020). A Benders decomposition approach for an integrated bin allocation and vehicle routing problem in municipal waste management. In: Rossit D.A., Tohmé F. & Delgadillo G.M. (Eds.), *Production Research. 10th International Conference of Production Research – Americas, ICPR-Americas 2020, Bahía Blanca, Argentina, December 9–11, 2020. Revised Selected Papers, Part 2.* Springer, Cham, Switzerland, pp. 3–18. **DOI:** https://doi.org/10.1007/978-3-030-76310-7_1.

Majid A., Novita E., Gusniani I. & Hartono D.M. (2021). Mapping of solid waste generation and collection by using GIS: A case study in Depok City. *IOP Conference Series: Earth and Environmental Science*, **716**, 012024. **DOI:** https://doi.org/10.1088/1755-1315/716/1/012024.

Marković D., Petrović G., Ćojbašić Ž. & Marinković D. (2019). A metaheuristic approach to the waste collection vehicle routing problem with stochastic demands and travel times. *Acta Polytechnica Hungarica*, **16**(7), pp. 45–60. **URL:** https://acta.uni-obuda.hu/Markovic_Petrovic_Cojbasic_Marinkovic_94.pdf [5.10.2021].

Mojtahedi M., Fathollahi-Fard A.M., Tavakkoli-Moghaddam R. & Newton S. (2021). Sustainable vehicle routing problem for coordinated solid waste management. *Journal of Industrial Information Integration*, **23**, 100220. **DOI:** https://doi.org/10.1016/j.jii.2021.100220.

Nuortio T., Kytöjoki J., Niska H. & Bräysy O. (2006). Improved route planning and scheduling of waste collection and transport. *Expert Systems with Applications*, **30**(2), pp. 223–232. **DOI:** https://doi.org/10.1016/j.eswa.2005.07.009.

Rabbani M., Farrokhi-asl H. & Rafiei H. (2016). A hybrid genetic algorithm for waste collection problem by heterogeneous fleet of vehicles with multiple separated compartments. *Journal of Intelligent and Fuzzy Systems*, **30**(3), pp. 1817–1830. **DOI:** https://doi.org/10.3233/IFS-151893.

Ramdhani M.N., Baihaqi I. & Siswanto N. (2018). Optimization of municipal waste collection scheduling and routing using vehicle assignment problem (case study of Surabaya city waste collection*). IOP Conference Series: Materials Science and Engineering*, **337**, 012013. **DOI:** https://doi.org/10.1088/1757-899X/337/1/012013.

Singh S. & Behera S.N. (2019). Development of GIS-Based Optimization Method for Selection of Transportation Routes in Municipal Solid Waste Management. In: Kalamdhad A.S., Singh J. & Dhamodharan K. (Eds.) *Advances in Waste Management. Select Proceedings of Recycle 2016*. Singapore: Springer, pp. 319–331. **DOI:** https://doi.org/10.1007/978-981-13-0215-2_22.

Tirkolaee E.B., Mahdavi I. & Seyyed Esfahani M.M. (2018). A robust periodic capacitated arc routing problem for urban waste collection considering drivers and crew's working time. *Waste Management*, **76**, pp. 138–146. **DOI:** https://doi.org/10.1016/j.wasman.2018.03.015.

Tirkolaee E.B., Mahdavi I., Seyyed Esfahani M.M. & Weber G.-W. (2020). A hybrid augmented ant colony optimization for the multi-trip capacitated arc routing problem under fuzzy demands for urban solid waste management. *Waste Management and Research: The Journal for a Sustainable Circular Economy*, **38**(2), pp. 156–172. **DOI:** https://doi.org/10.1177/0734242X19865782.

Xu X., Liang D., Chen X. & Zhou Y. (2015). A Risk Elimination Coordination Method for Large Group Decision-Making in Natural Disaster Emergencies. *Human and Ecological Risk Assessment: An International Journal*, **21**(5), pp. 1314–1325. **DOI:** https://doi.org/10.1080/10807039.2014.955394.

Vári A. (2000). Trends in decision making for the siting of waste management facilities. In: *Stakeholder confidence and radioactive waste disposal. Inauguration, First Workshop and Meeting of the NEA Forum on Stakeholder Confidence in the Area of Radioactive Waste Management. Paris (France), 28–31 August 2000.* Nuclear Energy Agency, Organisation for Economic Co-Operation and Development, pp. 71–73. **URL:** https://www.oecd-nea.org/upload/docs/application/pdf/2020-12/nea2829.pdf [5.10.2021].

Zeiss C. & Lefsrud L. (1996). Making or breaking waste facility siting successes with a siting framework. *Environmental Management*, **20**, pp. 53–64. **DOI:** https://doi.org/10.1007/PL00006702.