P-Graph approach for the optimisation of biomass supply network for biogas production in urban areas

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The utilization of anaerobic systems for biogas production integrates various aspects such as renewable energy generation, waste management, waste treatment, and biofertilizer production. This study introduces a model that focuses on the economic optimization of a biomass supply network for biogas production in urban areas. The selected feedstocks considered in the model are biowaste and residues sourced from restaurants, shops, and the food and beverage industry.

This study introduces two significant advancements. Firstly, it employs an enhanced GIS-based approach that integrates greenhouse gas (GHG) requirements by incorporating a maximal allowed transport distance. This integration aims to achieve minimal GHG savings from biogas usage. These GHG-based requirements align with the specifications outlined in Directive 2018/2001, which promotes the use of renewable energy sources and stipulates a minimum 80% reduction in greenhouse gas emissions from biogas plants operating from 2026, in addition to meeting environmental sustainability criteria. Secondly, the study introduces a novel approach that combines GIS mapping of biomass potential with a P-graph framework for optimizing the biomass supply network. This integration facilitates comprehensive and efficient optimization of the network for biogas production.

The model is developed and solved using P-Graph Studio, while feedstock availability and transportation distances are determined using the QGIS tool. The approach is tested under two scenarios: one with an annual production of 36,000 GJ and another with an annual production of 72,000 GJ. The p-graph approach enables the identification of the optimal economic solution for both scenarios. As the most of the biogas potential is concentrated in a single brewery, the specific cost of the biomass supply network, including feedstock and transport, remains comparable for both scenarios, with values of 12.44 EUR/GJ and 12.61 EUR/GJ for the second case.

1. Introduction

Renewable energy sources are recognised as crucial for the transition towards climate neutrality and the replacement of fossil fuels. Biogas is used as a source of heat, electricity, and transportation

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fuel and is becoming increasingly popular due to its ability to reduce greenhouse gas emissions, conserve resources, and provide a sustainable energy source. Biogas and biomethane production is steadily increasing over the last two decades [1]. Due to high yield and ease of cultivation and storage, maize silage is commonly used as a feedstock for biogas production. However, socio-economic concerns are raised due competition with land use, competition with food and feed production, as well as in the increase of the price of maize silage. Those concerns are reflected in Directive 2018/2001 which outlines several constraints for biogas production to ensure its sustainability and not having impacts on the environment and society. Among other limitations, the directive specifies that the GHG savings from the use of biomass for electricity, heating and cooling production should be at least 70% for installations starting operation from 2021 until the end of 2025 and 80 % for installations starting operation from 2026 [2]. Furthermore, the European Commission introduced a cap on food and feed crops toward the EU renewable objective, starting at 7% in 2021 and rapidly decreasing to 0% in 2030, to reduce the implications of Indirect Land-Use Change (ILUC). The given requirements, but also the increase in the price of the maize silage foster the need to shift towards sustainable alternatives of biogas feedstocks. Some examples of sustainable alternatives for maize silage are by-products from industry, supermarkets, fast food restaurants, agricultural residues and organic fractions of municipal biowaste. Those feedstocks are characterized by low energy density and in some cases, scattered feedstock generation. Hence, biomass potential assessment is an important step in the biomass-based analysis. The use of a Geographic Information System (GIS) for biomass potential mapping is recognised as beneficial as it offers several benefits, including improved decision-making due to enhanced analysis and visualization of data related to biomass potential, available infrastructure, biomass potential density analysis, identification of most promising locations for biomass processing (biogas site) and many others. In the literature, there are numerous papers that prove the benefits of GIS utilization for biogas production mapping and the untapped potential of alternative feedstocks for biogas production. Some of the most recent advancements are presented in the next paragraph.

In their recent paper, Romero et al. [3] integrated fuzzy logic with GIS to define suitable locations for a potential biorefinery implementation. Ukova [4] et al. used the GIS approach for assessing the biomass energy potential and identification of appropriate biomass conversion technologies in Nigeria. In their work, Rhofita et al. [5] performed a GIS mapping analysis of the biomass potential of agricultural and forest residues in Indonesia. Similarly to this, Chakraborty et al. [6] developed a GIS map of crop residue potential for energy utilization in biomass/biofuel power plants.

The aforementioned studies have shown that biomass may provide a significant contribution to the transition towards renewable energy solutions. However, the cost of biomass supply networks and technologies to convert biomass into useful forms of energy is often a barrier to increased utilization of biomass for biogas production. To address this barrier, significant research efforts are being made. It has been noted that graph theory methods are increasingly used in supply network optimisation problems. In mathematics and computer science, graph theory is the study of graphs, mathematical structures used to model pairwise relations between objects from a certain collection. Process-graph (or P-graph) is a unique bipartite graph representing the structure of a process system [7]. P-graph optimization can be applied to a wide range of domains and problem types. The utilization of the P-graph approach brings forth several advantages, including the unambiguous representation of decision alternatives, the generation of a mathematical model through algorithms, a decrease in solution procedure complexity, and the ability to derive multiple alternative solutions. It has been successfully used in various areas, including scheduling and resource allocation problems, task and data parallelism, parallel algorithm design, and optimization of parallel computing systems. Its versatility makes it a valuable tool for addressing different optimization challenges across different disciplines. Adonyi et al. [8] applied a p-graph framework for the optimisation of the maintenance schedule for public transportation buses. Similar to this, Bartos et al. [9] implemented a p-graph approach for the optimisation of a production line in the assembly industry. Tan et al. [10] developed a P-graph model for the synthesis of hydrogen networks. The developed model included direct reuse/ recycle and regeneration schemes. Ji et al. [11] developed a P-graph model for the optimization of hydrogen and battery energy storage. The model he developed used a multi-period modelling approach to reduce and compare costs of those two storage systems.

P-graph application is especially interesting for biomass supply network optimization problems. How et al. [12] developed a decomposition approach for a p-graph application of synthesis of multiple biomass corridors. Stile et al [13] have expanded the use of P-graph-based algorithms to assess the reliability of raw material availability. Malladi et al. [14] have developed a p-graph-based decision support tool for optimizing the short-term logistic of forest-based biomass, by minimizing the biomass logistics cost. Egieya et al [15] used a P-graph framework to optimise the integrated biopower supply network, by maximizing the economic performance. Lo et al. [16] proposed a P-graph based method that considered the incorporation of biomass supply chain uncertainties. Results have shown that a reduction in net present value (NPV) ranges from 1.39% to 12.21% when the biomass shortage scenario was included. Ondruška et al. [17] extended the application of the P-graph approach to perform resource optimization in an aquaponics facility.

Interest in biomass supply network optimization is evidently increasing. However, to exploit the potential of the waste materials for biogas production, it is crucial to link the availability of biomass and its geographical distribution, with the optimization of the economical performances of a biomass supply network. Furthermore, a limitation requested by the EU legislation [2] should not be neglected in this process and mathematical models developed for potential assessment and biomass network optimization should integrate limitations regarding the minimum GHG savings, compared to fossil fuel comparator. To address this research gap and integrate these crucial factors for the successful real-life application of waste materials for biogas production, this paper provides the following novelty:

- enhanced GIS-based approach that integrates GHG requirements in terms of maximal allowed transport distance (to achieve minimal GHG savings from the use of biogas);

- a novel approach that combines GIS mapping of biomass potential and a P-graph framework for biomass supply network optimization.

2. Method

The first part of this method is focused on conducting a GIS mapping of biomass potential. It is an important part as it enhances understanding of the availability of feedstocks for biogas production, its geographical dispersion and the transport distance between feedstock providers and biogas sites. Within the GIS mapping, an evaluation of feedstock which fulfills GHG savings of 80% will be conducted. The results of this part of the research will be used for p-graph-based optimisation of a biomass supply network, which represents the second part of this research. The method is presented in the flowchart in Figure 1 and described in the subsection below.

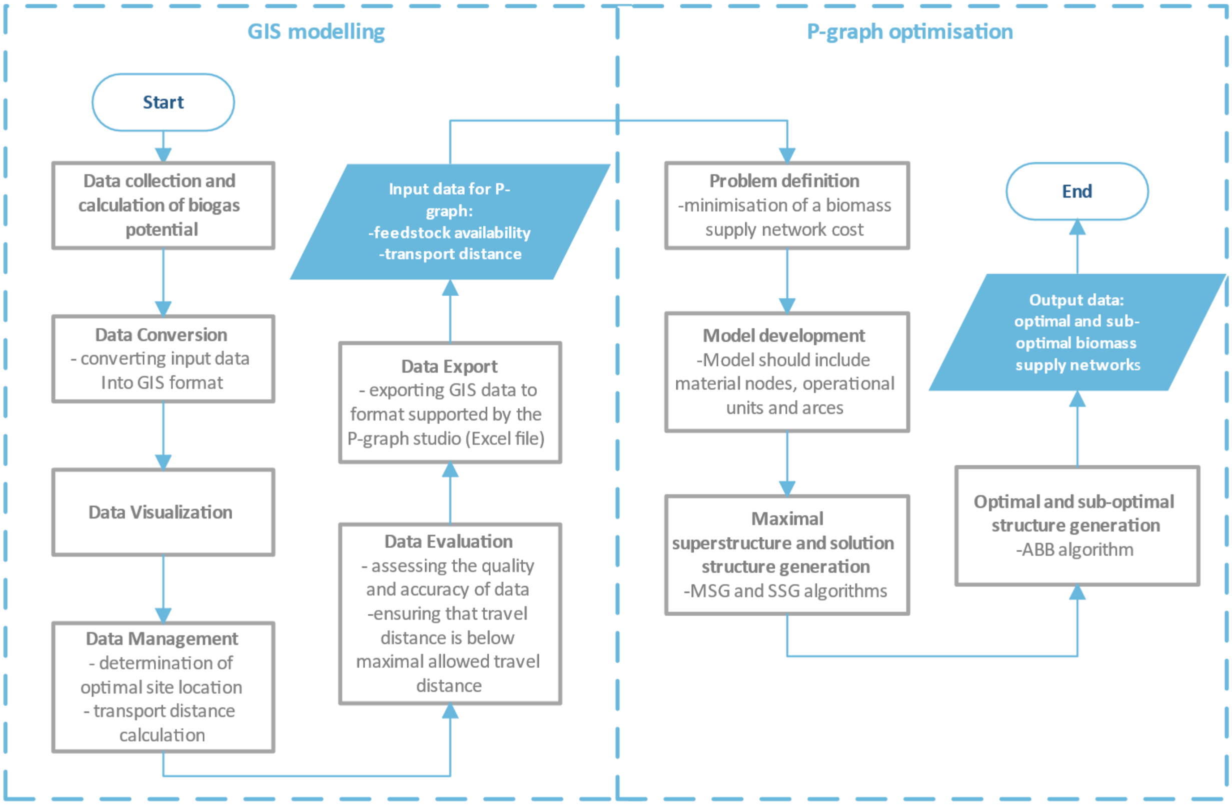

Figure 1 Flowchart representation of the method

As described in the Introduction, the method novelties of this paper include integration of GHG requirements in terms of maximal allowed GHG emissions from transport (to achieve minimal GHG savings from the use of biogas) in the GIS modelling step, as well as linkage of GIS mapping of biomass potential and a P-graph framework for biomass supply network optimization.

2.1 GIS potential assessment

The process of GIS potential assessment involves data collection, data conversion, data analysis, data visualization, and data management. The steps of this process can be tailored to meet the specific needs and requirements of different types of requirements.

2.1.1. Collection of data on biogas potential

The first step in using GIS for biomass mapping is to gather data on the potential biomass resources in the area of interest. For the urban areas, the analysed feedstock can include biodegradable waste from supermarkets, fast food restaurants and organic fraction of waste from industry, among others. This step includes identifying and quantifying the types, amounts and sources of feedstock eligible for biogas production generated in a specific area. In this step, feedstocks eligible for biogas production are determined and their respective biogas potential is assessed. In the scope of this work, the following waste materials and by-products are considered:

- Industry biowaste
- Oil and fat
- Spent grain.

The required data could be collected from waste registers, statistic registers, environmental impact assessment reports, etc. Automatised collection of information on locations of supermarkets, fast food restaurants and industries is possible via Quick OSM Plugin, which is available in the QGIS tool [18]. This Plugin enables the export of data from the Overpass server [19] that integrates data from the geographic database Open Street Maps [20].

2.1.2. Data Conversion

Once the data has been collected, it must be converted into a format that can be used in a GIS. This typically involves converting the data into a digital format, such as a shapefile or a raster image, that can be imported into the GIS software. As the considered feedstocks occur at specific locations (in industry, fast food restaurants, etc), data conversion refers to the process of taking a physical address, such as a street address and postal code and converting it into a set of geographic coordinates, such as latitude and longitude. The resulting geographic coordinates are used to locate and map addresses on a digital map.

2.1.3. Data Visualization

The results of the data conversion can be visualized using a GIS. This includes creating maps that show the distribution of biomass resources, where different colours and different sizes indicate the potential of different feedstock providers. A more detailed description of GIS mapping is provided in the authors' earlier papers [21], [22].

2.1.4. Data Management

Data collected, converted to GIS format and visualized in previous steps can be future managed to obtain the required input data for P-graph optimisation. For the cases of biogas utilization, optimal biogas site location is insightful information. Optimal biogas site location selection in GIS involves evaluating proximity to potential biogas sources. However, in urban areas, the location of a biogas plant is often constrained by the General urban plan. Therefore, for urban locations, it is advisable to set a location next to an existing landfill or composting plant. Based on the location of biogas providers and the location of the biogas site, transport distance can be assessed. This can be done via the “Shortest path” query in QGIS. The shortest path in QGIS is a route-finding analysis that determines the quickest or shortest path from a starting point (feedstock providers) to an endpoint (biogas site) through a network of interconnected lines, representing transport routes. Transport distance is an important element to consider for feedstock utilization, as it influences both associated GHG emissions and transport costs In the scope of this work, the transport distance is based on the shortest path. The transport distance is used to assess the transport cost, as presented in Equation (1):

$$C_{trans} = \frac{d\ (K_{full} + K_{empty})}{B_{biogas}} \times b \times\ T \tag{1}$$

Where C_{trans} represents specific transport cost (EUR/GJ), d transport distance (km), K_{full} fuel consumption of loaded truck (l/km), K_{empty} fuel consumption of an empty truck (l/km), b fuel price (EUR/l), B_{biogas} for biogas potential of transported feedstock (GJ) and T for transport cost correction factor. In this work, it was assumed that T equals 3, meaning that the cost of fuel is one-third of the total transport cost. This assumption is based on the calculation of the Joint Research Centre presented in their report “Estimating road transport costs between EU regions” [23]. When calculating the fuel cost, the average cost of diesel for the last two years was taken as the reference.

2.1.5. Data evaluation

GIS data evaluation is a critical step in the process of using geographic information system (GIS) technology. The evaluation process involves assessing the quality and accuracy of the data that is being used to create maps, perform analysis, or make decisions. This evaluation helps to ensure that the results of GIS analysis are accurate and reliable, and that the data being used is suitable for the intended purpose. It may also involve checking the data against other sources to validate its accuracy and identifying and correcting any errors or inconsistencies in the data.

As explained in the Introduction, GHG savings for biogas plants starting from 2026 must be at least 80% compared to fossil fuel comparator. The minimum GHG savings can be used for determining the maximal transport distance of feedstock for biogas transportation. To ensure that the transport distance is below the given limit, the transport distance should be evaluated for each considered site that provides feedstock. Additionally, is important to note that maximum transport distance differs for the different feedstock groups and should be calculated based on the Method defined in Directive 2018/2001. The evaluation of maximum transport distance is implemented in two steps. In the first step, the information on the maximum distance is associated with each considered feedstock group. The grouping of the feedstocks and comparison with the maximum travel distance can be implemented with “Select features by using an expression” and “Field calculator”. The implementation of this step before the P-graph optimization eliminates the future need to include GHG limitation in p-graph optimization.

2.1.6. Data export

Data obtained via QGIS will be further as the input data for the P-graph optimization. Hence, GIS data should be exported to a data format supported by the P-graph studio, which is Excel file format. The first step for this is exporting data from QGIS to comma-separated values (CSV) file format, which is a plain text format that stores tabular data with each row representing a feature and each column representing an attribute. This process allows users to extract and transfer attribute data from spatial layers in QGIS for further analysis or sharing with other software or users. To export CSV to Excel, the obtained file can be opened directly in Excel and saved as an Excel file. Excel will provide step-by-step instructions during the import process, enabling to specify the delimiters, column formats, and other settings necessary for accurately interpreting and displaying the data from the CSV file.

2.2 P-graph

The P-Graph optimization method is a mathematical optimization technique that can be used to optimize the biomass supply network. The following is a method for using P-Graph optimization to optimize the biomass supply network:

2.2.1. Problem definition

The first step in using P-Graph optimization is to define the problem that needs to be solved. This involves identifying the objectives of the optimization, such as minimizing costs, maximizing profit, maximizing efficiency, and defining the constraints, such as available biomass resources, transportation capacity, and demand for biomass. In the scope of this work, the objective function is to minimize the cost of a biomass supply network.

2.2.2 Model development

The next step is to develop a mathematical model of the biomass supply network. This model should include all relevant variables, such as biomass production, transportation, and utilization, as well as the constraints and objectives. The P-Graph optimization method uses a graph-based representation of the network to model the relationships between the variables and the constraints. In this representation, material nodes are used to represent raw, interim and final materials, while operating unit nodes are representing transportation, processing, and anaerobic digestors. Anaerobic digesters are enclosed structures where the anaerobic break down of raw material (feedstock) takes place. Arcs in P-graphs are directed edges that represent relationships between nodes in a network graph. In a P-graph, arcs represent a one-way flow of resources, or dependencies between nodes and they can have different lengths, capacities, or costs associated with them. In this work, the model is being developed in the P-graph studio.

2.2.3 Maximal superstructure and solution structure generation

Once the model has been developed, it can be solved using P-graph-based algorithms. Algorithm Maximal structure generation (MSG) yields the maximal structure, i.e., the superstructure, for the Process Network Synthesis (PNS) problem. The generated superstructure incorporates each combinatorically feasible process structure. MSG algorithm is followed by the solution structures generator, known as algorithm SSG. The SSG exhaustively identifies all combinatorically feasible solution structures that satisfy five axioms. A detailed description of those axioms is described in the literature by professors F. Friedler and L.T. Fan [24], founders of the P-graph framework. Those feasible structures are used for future evaluation and optimization.

2.2.4 Optimal and sub-optimal structure generation

Finally, algorithm ABB (an accelerated branch and bound algorithm) will be used to generate the optimal structure together with a ranked list of suboptimal structures. The objective function here is to minimize the cost of a biomass supply network. Hence, the structure with the lowest cost to the biomass supply network is the optimal one.

3. Case study

The Croatian capital city of Zagreb served as the case study for the presented method. The locations considered for this case study are shown in Figure 2.

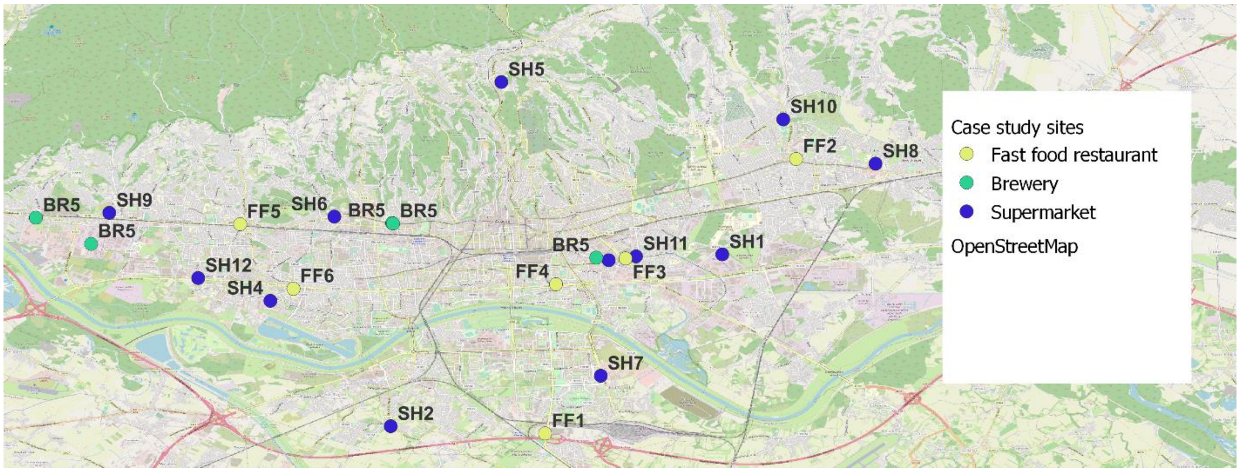

Figure 2 Case study Sites

The input data from Table 1 were applied to compute the cost of the feedstock.

Table 1 Specific feedstock cost

Feedstock	Cost (EUR/t)
Spent grain	33 [25]
Industry biowaste	0
Oil and fat	0

4. Results

According to the method stated in the Method section, the biogas potential from spent grain, industrial biowaste, oil, and fat was determined for the considered supermarkets, fast food chains, and breweries. The location of the biogas site was selected following the location of the existing composting plant and landfill. In accordance with the selected location, the transport distances between supermarkets, fast food restaurants, breweries and the biogas site were determined, as represented in Figure 3. The transport distance was calculated for each site that provides feedstock to the biogas plant. In this analysis, the assumption was made that trucks would be utilized for transporting the feedstock. The selected roads, determined as the shortest routes, are permissible for truck travel. Moreover, only feedstocks with transport distances below the maximum allowed distance (to achieve the necessary GHG savings) were considered for future evaluation.

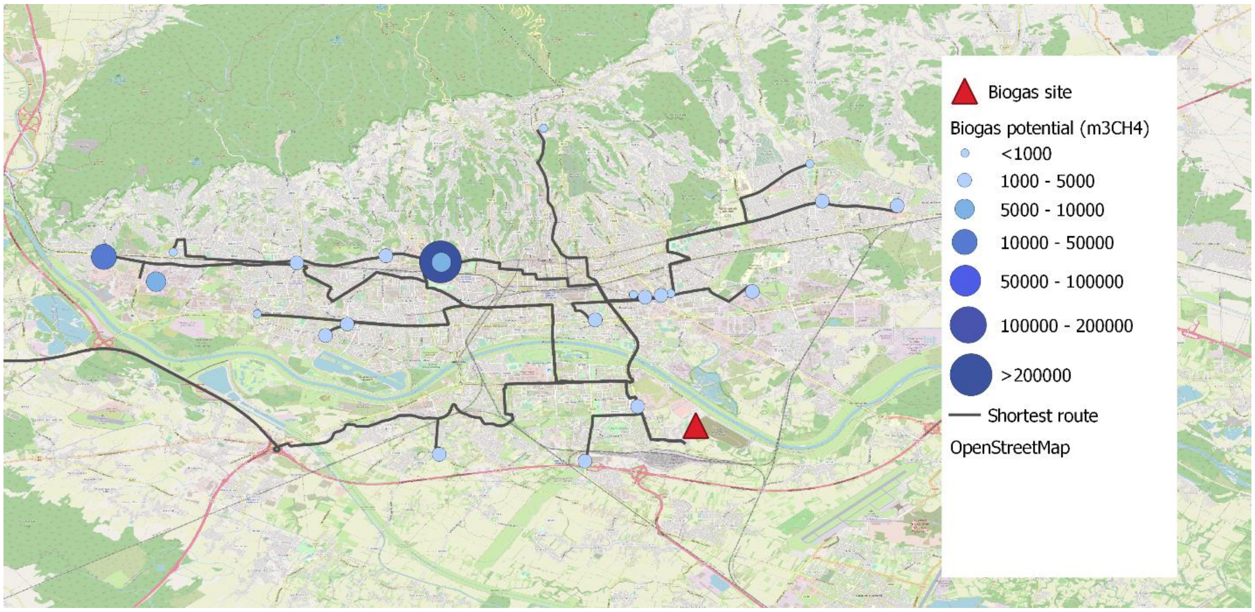

Figure 3 Transport road route and optimal biogas site location

As seen in Figure *3*, biogas potential significantly varies between different feedstock-providing sites. For the considered case study, the greatest biogas potential comes from breweries. As explained in the Method section, GIS data represented in Figure *3* were converted to a format supported by P-graph Studio (Excel file) and used as the input data for P-graph-based optimisation The list of these sites, along with the respected abbreviation used for the P-graph representation and transport distance is presented in Table 2.

Table 2 P-graph, legend and transport distance

Site	Abbreviation	Distance (km)
Supermarket	SH1	9.4
Supermarket	SH2	10.5
Supermarket	SH3	33.4
Supermarket	SH4	12.9

Supermarket	SH5	12.2
Supermarket	SH6	11.8
Supermarket	SH7	1.9
Supermarket	SH8	15.2
Supermarket	SH9	17.6
Supermarket	SH10	14.4
Supermarket	SH11	7.3
Supermarket	SH12	14.3
Supermarket	SH13	6.7
Fast food restaurant	FF1	4.3
Fast food restaurant	FF2	13.5
Fast food restaurant	FF3	7.1
Fast food restaurant	FF4	7.5
Fast food restaurant	FF5	14.5
Fast food restaurant	FF6	12.4
Brewery	BR1	10.8
Brewery	BR2	18.5
Brewery	BR3	18.9
Brewery	BR4	10.8
Brewery	BR5	6.8

Figure 4 displays a P-graph representation of the case study's maximal structure. As described in the method, the material nodes are represented raw materials (feedstock) and the final product (biogas). Operational units are representing feedstock transportation. As this analysis assumes that the specific cost of anaerobic digestion will not differ between the considered feedstock materials, the cost of the anaerobic digestion was not a variable (and operating unit) included in the determination of the minimal biomass supply network cost.

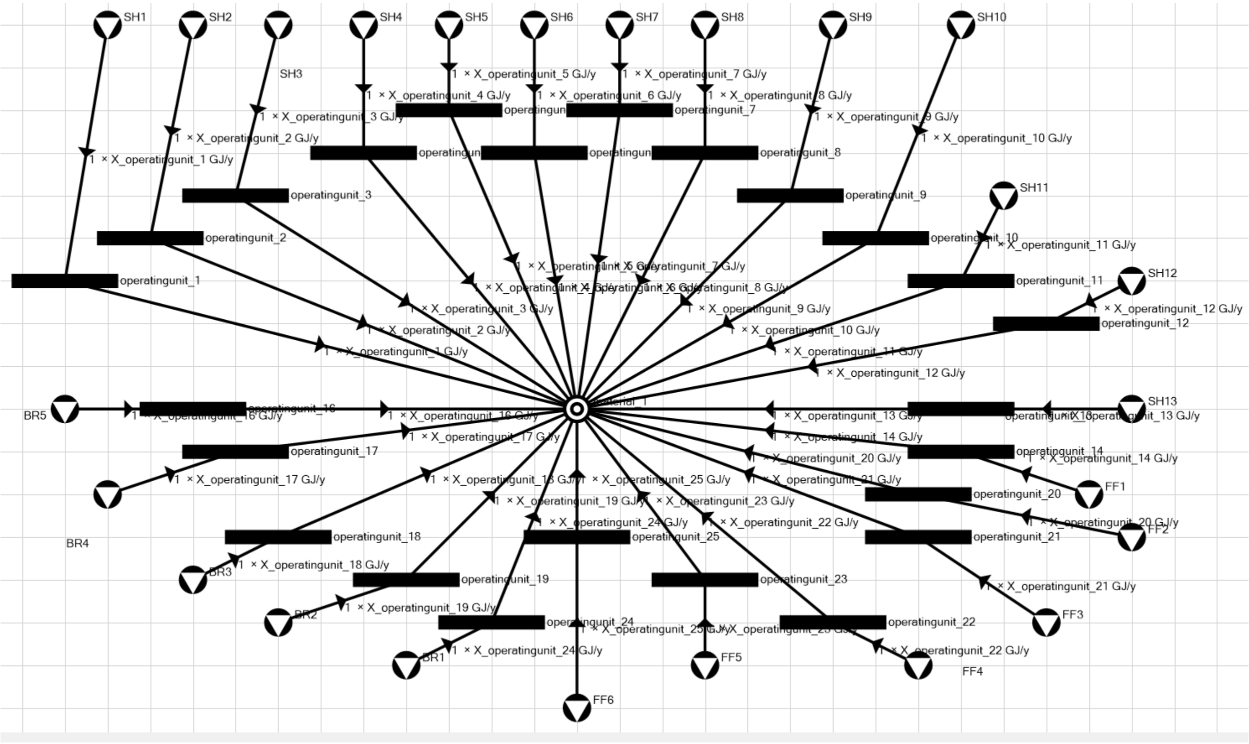

Figure 4 P-graph representations of the maximal structure of the case study

Based on the maximum structure and input data obtained from the GIS tool, optimal and suboptimal structures were defined. Here, the objective function is to minimise the cost of the biomass supply network. Additionally, it is important to note that the main purpose of this structure optimization is to compare the economic viability of the utilization of different biomass supply structures. Consequently, only the costs that differ between different biomass supply structures are included in this analysis.

The optimal and suboptimal structures were defined for two cases which correspond to the biogas production required to power a Combined Heat and Power (CHP) engine with electric power of 0.5 MW_{el} and 1 MW_{el}. For the first case, this corresponds to annual biogas demand of 36,000 GJ/y, and for the second to annual biogas demand of 72,000 GJ/y. The base for two demand-side scenarios is to quantify the influence on the price for the cases with different demands. The optimal structure for annual biogas production of 36,000 GJ/y is shown in in Figure 5.

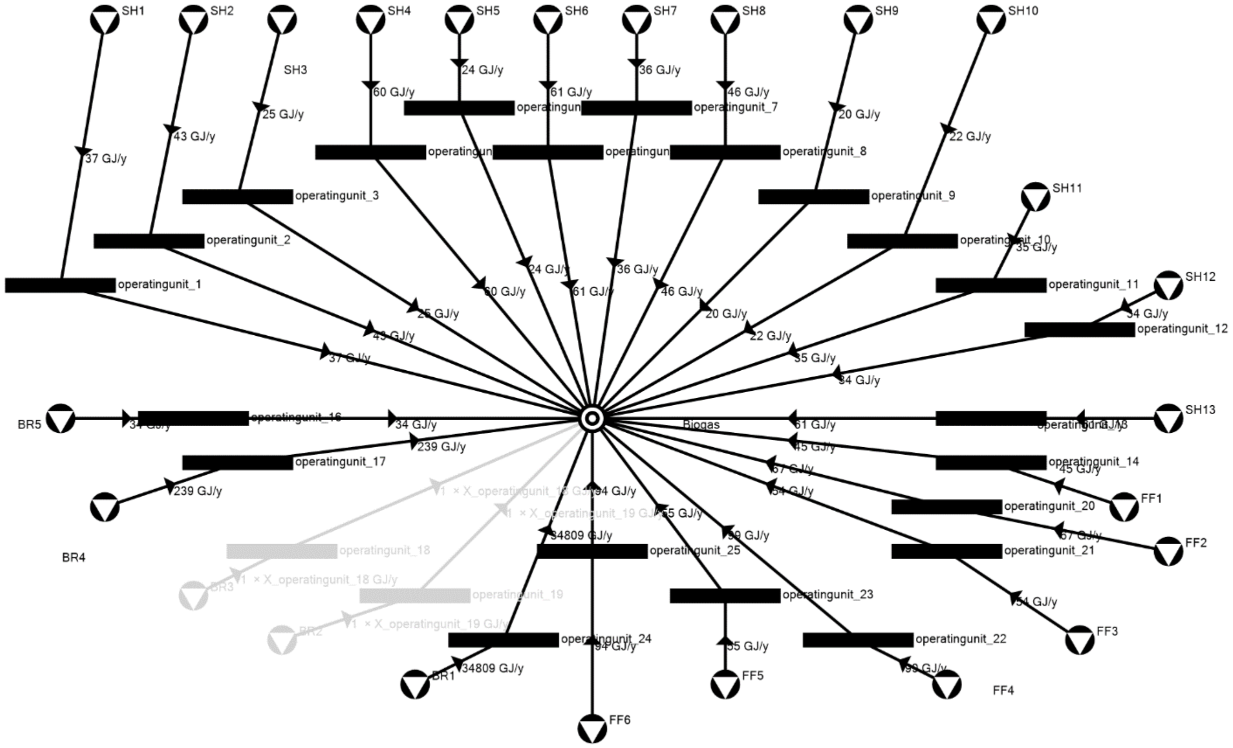

Figure 5 The optimal structure for annual biogas production of 36,000 GJ/y

The cost of the biomass supply chain (including feedstock and transport costs) is 448,080 EUR. This equals 12.44 EUR/GJ. The data from the optimal structure (Figure 5) are presented in Table 3, to improve the visibility of the numbers. As seen in Figure 5, feedstock sites that provide waste materials (supermarkets and fast-food restaurants) are prioritised as feedstock suppliers. The optimal structure for annual biogas production of 72,000 GJ/y is presented in Figure 6.

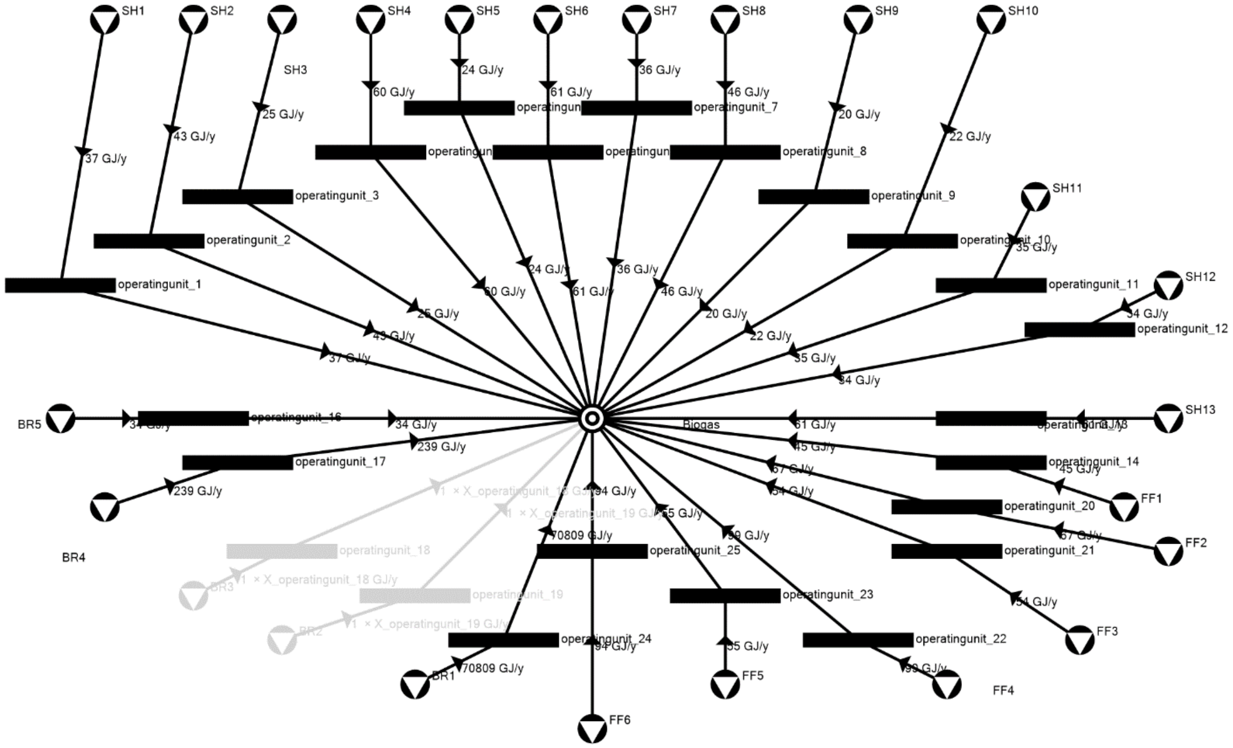

Figure 6 The optimal structure for annual biogas production of 72,000 GJ/y

The cost of the biomass supply chain (including feedstock and transport costs) is 907,593 EUR. This equals 12.61 EUR/GJ. The data from the optimal structure (Figure 6) are presented in Table 3**Error! Reference source not found.** to improve the visibility of the numbers.

Table 3 The optimal structure for annual biogas production of 36,000 GJ/y (S1) and 72,000 GJ/y (S2)

Site		SH1	SH2	SH3	SH4	SH5	SH6	SH7	SH8	SH9	SH10	SH11
S1	**Delivered feedstock (GJ/y)**	37	43	25	60	24	61	36	46	20	22	35
S2		37	43	25	60	24	61	36	46	20	22	35
Site		SH12	SH13	FF1	FF2	FF3	FF4	FF5	FF6	BR1	BR4	BR5
S1	**Delivered feedstock (GJ/y)**	34	62	45	67	54	99	55	94	34809	239	34
S2		34	62	45	67	54	99	55	94	70809	239	34

The utilization of waste materials from supermarkets and fast-food establishments is evident in both scenarios, as indicated in Table 3. However, their contribution is relatively low due to the limited potential of these sites. It is noteworthy that the specific cost of biomass supply is slightly higher in the second case, primarily because of a dominant supplier (brewery) with the highest biogas potential. Consequently, this supplier significantly influences the average price of the biomass supply chain. The increased demand for biogas leads to a further rise in the specific cost of the biogas supply network. Thus, it can be inferred that the economic viability of biogas production in urban areas should rely on waste materials to enhance its feasibility.

The combination of integrating GIS mapping of biomass potential and employing a P-graph framework for optimizing biomass supply networks, implemented in this work and tested in the case study proved to be effective. This approach improves the accuracy of input data and consequently results, in comparison with other studies that consider biomass potential to be generated from a single site [11] or clustered into zones [26].

Furthermore, the elimination of feedstock suppliers with high greenhouse gas (GHG) emissions from transport during the initial step of GIS mapping has demonstrated its efficiency by ensuring that the utilization of the final product, namely biogas, achieves at least the minimum GHG savings. However, this approach's applicability is limited to cases where the transport distance is the sole factor affecting GHG emissions, and typical values can be used to calculate other GHG-related factors. For more complex situations where total GHG emissions may vary based on selections made within the supply chain network, a more intricate integration of GHG emissions savings limitations is required.

5. Conclusions

The method employed in this study integrates GIS mapping and graph theory approaches. GIS mapping is utilized to assess the availability and geographical distribution of feedstocks for biogas production, as well as to determine the transport distance between feedstock providers and the biogas facility. Additionally, the GIS tool is used to evaluate the suitability of feedstocks for biogas production based on their transport distance and the maximum allowable greenhouse gas (GHG) emissions allocated for feedstock transportation, in line with the requirements outlined in Directive 2018/2001. These limitations are incorporated as part of the input data to develop the maximal structure and optimize the biomass supply network using a p-graph approach. The objective of this optimization is to minimize the overall cost of the biomass supply network.

The proposed approach is implemented and tested in a case study conducted in an urban area in Zagreb, focusing on biowaste, residues, and by-products from supermarkets, fast food restaurants, and breweries. Two scenarios are considered, one with an annual production of 36,000 GJ and the other with an annual production of 72,000 GJ. The P-graph approach enabled the identification of the optimal economic solution for both cases. Since the majority of the biogas potential is concentrated in a single brewery, the specific cost of the biomass supply network (including feedstock and transport) remains similar for both scenarios, at 12.44 EUR/GJ and 12.61 EUR/GJ for the second case. The results reveal that the specific cost of the biomass supply network is relatively high, primarily due to the significant contribution of spent grain in biogas production.

This research is expected to be beneficial to decision-makers and biogas plant operators in the development of the biogas industry. To enhance the economic feasibility of biogas production, it is crucial to explore additional sources of waste materials and prioritize the utilization of such materials in biogas production. Future studies should aim to expand the range of eligible feedstocks for biogas production, thus enhancing the economic feasibility of this process.

Acknowledgement

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