WARSAW UNIVERSITY OF TECHNOLOGY Index 351733	DOI: 10.24425/ace.2025.154108
FACULTY OF CIVIL ENGINEERING COMMITTEE FOR CIVIL AND WATER ENGINEERING	ARCHIVES OF CIVIL ENGINEERING
POLISH ACADEMY OF SCIENCES ISSN 1230-2945	Vol. LXXI ISSUE 2 2025

 pp. 67 –82

Research paper

An approach to transport infrastructure design using a two-step method based on modified ant colony optimization

Mariusz Korzeń[1], Maciej Kruszyna[2]

Abstract: The main purpose of the paper is to develop a tool to effectively support the transport infrastructure planning process. The novel method is based on modified ant colony optimization and is used for evaluating new infrastructure sections in the public transport. The section could contain a single route as well as a combination of two or more routes. The authors propose a two-step evaluation. Step one uses a modified ant colony optimization to evaluate a single underground route. As a result, for each route, the effort that artificial ants have to cover the routes is obtained. Such effort is calculated considering the distance, total length, number of inhabitants, and areas with access to the rail network. In step two, the proposed routes are combined to create variants. The evaluation of combining routes use additional parameters like crossing time or travel time in alternative means. The case study located in one of the biggest agglomerations in Poland shows the method's utility in the evaluation of options for a railway tunnel. The analyses show that all criteria have an influence on the results and that the new, two steps method gives an intriguing effect. The presented methodology contains novel elements and their implementation to specific transport infrastructure elements. The results are contrasted with an algorithm based on multi-criteria analysis, which showed the greater complexity of the proposed approach.

Keywords: modified ant colony optimization, public transportation, railway tunnel, transport infrastructure, two-step evaluation

[1]PhD., MSc., Wroclaw University of Science and Technology, Faculty of Civil Engineering, ul. Wybrzeże Wyspiańskiego 27, 50-370 Wroclaw, Poland, e-mail: mariusz.korzen@pwr.edu.pl, ORCID: 0000-0002-6442-7279
[2]DSc., Associate professor., Wroclaw University of Science and Technology, Faculty of Civil Engineering, ul. Wybrzeże Wyspiańskiego 27, 50-370 Wroclaw, Poland, e-mail: maciej.kruszyna@pwr.edu.pl, ORCID: 0000-0001-8876-6307

1. Introduction

The process of transport planning is very important and aims to properly develop transport supply systems [1, 2]. In the case of public transportation, this is a complex process that consists of many elements such as line planning, frequency determination, vehicle number planning and crew planning. In the context of rail transportation, network planning is strongly constrained by existing infrastructure. Therefore, when considering rail network planning, the process should be preceded by an analysis of the creation of new routes. Many times in cities the problem is the lack of track in the downtown area, and thus the lack of rail accessibility. The problem is significant because in the city center are usually located traffic generators, that is, places where people want to get to. Thus, the attractiveness of this mode of transportation decreases. The development of a new route is associated with high costs, and an unsuitable route may not bring an increase in demand for the railroad.

In urban agglomerations, it is particularly important to adequately develop the public transport system. The main characteristics of efficient public transportation are rapidity, reliability, convenience and cost-effectiveness. Using the above characteristics, it is possible to move efficiently within the agglomeration. This is difficult to do and many problems can still be encountered in this aspect. Therefore, the issue of improving the public transport system is the subject of much analysis and research. The public transportation planning process can take place, for example, through a preliminary assessment of current technical and economic solutions [3–5] or through a multi-criteria coordinated model based on economic, social and environmental data [6]. It is important to keep in mind the mobility policy understood as the correction of the modal split into the sustainable proportion between car and non-car journeys [7]. Integral to mobility policy is the idea of mobility nodes as objects with more functions than just transport [8]. A possible solution to growing urban congestion is also the integration of different modes of transportation [9].

Heuristic methods are used to solve complex transportation problems [10]. These are problem-solving techniques that use trial and error, rule-of-thumb, and practical experience to find solutions to complex problems. Unlike traditional optimization methods, heuristic methods can provide near-optimal solutions to large and complex problems in a shorter time frame. In [11], the authors propose a heuristic method for designing a transit route network, taking into account a number of important parameters such as budget constraints, level-of-service standards, and attractiveness of transit routes. Particle Swarm Optimization (PSO) is used for optimization and an example of its application is described in [12–14]. It is possible to combine heuristic methods to create hybrid solutions [15]. Heuristic methods are also applicable in rail transportation problems. In [16], the authors compared a genetic algorithm with Bayesian Optimization in the field of rail network optimization. A review of the literature on applications of artificial intelligence in railroad systems is described in [17].

The tool used in this paper is the modified ant colony optimization (MACO). The "classic" version of the algorithm without modification (ACO) is also used in transportation problems [18]. The algorithm can be used to determine the optimal travel route [19, 20]. The authors indicate that this approach results in a complex for real-world applications, mainly because there are a huge number of variables and constraints. In addition, different types of data are required. The proposed algorithm yielded reasonably optimal solutions in cases where volume-dependent and length-dependent costs are the main contributors to the objective function. It is possible to optimize the entire transportation network [21–23] and plan multimodal routes [24]. In [25, 26], the authors use ACO to plan train traffic.

Researchers choose to modify the ACO to take benefit of its advantages, while adapting the algorithm to the problem under consideration in order to obtain the substantial results. In [27–29], the authors use an improved ACO to solve the vehicle routing problem (VRP). The authors in [30] presented a hybrid algorithm based on the ant colony algorithm for the HFFOVRP problem (the fixed fleet heterogeneous open vehicle routing problem), which is a more practical version of the VRP problem. This algorithm uses only a global pheromone update to search the feasible space more efficiently and takes into account the minimum pheromone value at the edges. In [31], the ACO is improved to suit the last-mile distribution by modifying the heuristic information, the update rules of pheromone, solution construction and local search strategy. In [32], an improved ant colony algorithm is developed for path planning based on a weight matrix, whereby the algorithm avoids multiple selection of paths with lower weights. It is also possible, using modifications, to optimize the urban bus network based on existing bus routes [33].

Many of papers consider the problem of routing without analyzing new infrastructure sections to optimize the network. The input of this paper is that we consider a two-step method based on MACO to evaluate new infrastructure sections. In addition, the proposed method allows more than one infrastructure section to be assessed under a single variant, which is important in the context of optimizing the entire transport system. The criteria used in the presented method are universal and can be applied to all transport modes.

MACO was first presented in [34] to evaluate railroad underground single-route proposals. The modification of the algorithm allows more parameters to be taken into account, such as the location of traffic generators in the city center, the number of inhabitants located adjacent to stations, and the number of streetcar or bus lines integrated with the railroad. The proposed evaluation method does not allow for the evaluation of combined routes. Therefore, the authors propose a two-step evaluation method that allows combining routes into variants.

2. Methodology

In order to be able to evaluate proposals consisting of more than one route, the authors proposed a novel two-stage evaluation method using MACO. The method is based on an ant colony system, with the main objective of finding the shortest path. In this paper, the authors' modification of ACO is based on an approximation of the objective function. That is, on the transition probability: instead of using the shortest path as an approximation, effort is used. This makes it possible to add multiple parameters that will shorten or lengthen the distance between nodes, so that it is possible to evaluate routes of different lengths and thus the results obtained are more meaningful. In the proposed method, in step one for each route, the effort that the artificial ants have to cover is obtained. In step two, the proposed routes are combined to create variants. The combining of routes is done using additional parameters. The entire evaluation process is shown in Fig. 1 and details are described in the following sections.

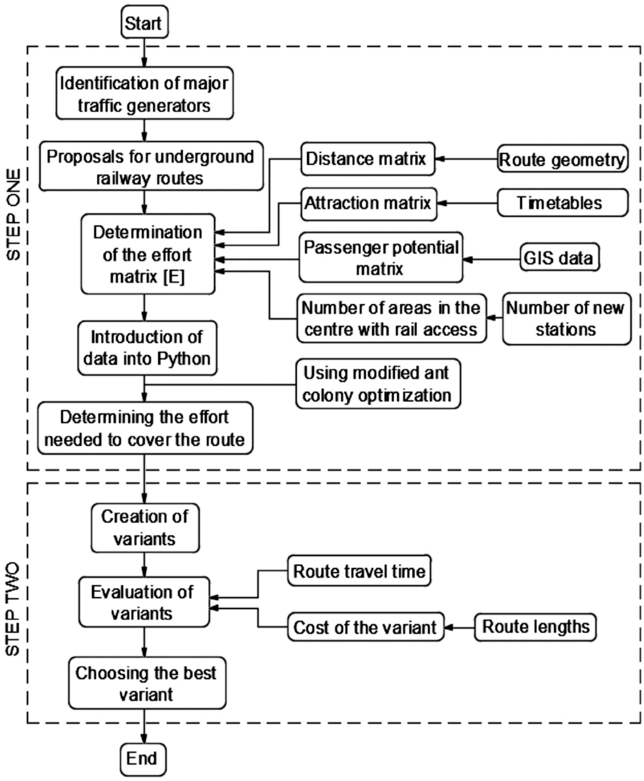

Fig. 1. Flow chart for finding the best variant of routes

2.1. Step one

The basis for step one is to use MACO. The "classical" ACO is a metaheuristic technique inspired by the behavior of certain ant species that build potential solutions by using (artificial) pheromone information that is adapted based on the ants' search experience and possibly available heuristic information [35]. In nature, a single ant cannot survive on its own, but as a group, ants are capable of solving complex problems and efficiently obtaining food for their colony. It is worth noting that ants can see very poorly, at a few centimeters. As a result, ants communicate with each other using a chemical called pheromone. Ants move at random, choosing a path with probability p_{ij}^k determined by the following formula:

$$p_{ij}^k = \frac{\left(\tau_{ij}^{\alpha}\right)\left(\eta_{ij}^{\beta}\right)}{\sum_{z\epsilon \text{allowed}_i}\left(\tau_{ij}^{\alpha}\right)\left(\eta_{ij}^{\beta}\right)} \tag{2.1}$$

where: p_{ij}^k – probability of a k-ant crossing through section ij; τ_{ij} – the amount of pheromone at section ij, η_{ij} – the attractiveness of section ij.

In transportation issues, η_{ij} is determined by the following formula:

$$\eta_{ij} = \frac{1}{L} \tag{2.2}$$

where: L – the total route to be taken.

Coefficient α is the parameter increasing η_{ij}. The larger α the more we "trust" the information left by other ants. It is assumed that $\alpha \geqslant 0$. Coefficient β is the parameter increasing η_{ij}.The larger β is, the more we 'trust' our own experience. It is assumed that $\beta \geqslant 1$. The user of the algorithm can freely control the parameters α and β. During migration, ants secrete a constant amount of pheromone for other ants to follow. The amount of pheromone left behind can be determined by the following formula:

$$\vartriangle \tau_{ij}^{k} = \begin{cases} Q/L_k \\ 0 \end{cases} \tag{2.3}$$

where: Q – a fixed value indicating the amount of pheromone, L_k – the length of route travelled by k-ant.

If the k-ant passes through segment *ij*, the value of the coefficient $\Delta\tau_{ij}^{k}$ takes the value Q/L_k. In other cases, where the ant has not walked the path and has left no pheromone, the coefficient $\Delta\tau_{ij}^{k}$ takes the value 0. When determining the route, it is necessary to update the amount of pheromone. The pheromone updating process can be divided into two parts. The first part is the reduction of the pheromone located along section ij due to the natural evaporation of the pheromone. The second part is the increase in pheromone due to the following ants crossing in the next iteration. The amount of pheromone located along section *ij* after the update can be described by the following formula:

$$\tau'_{ij} = (1-\rho)\,\tau_{ij} + \sum_{k} \Delta\tau_{ij}^{k} \tag{2.4}$$

where: τ_{ij} – the existing amount of pheromone at section *ij*, $\Delta\tau_{ij}^{k}$ – the amount of pheromone left by k-ant in the next iteration, ρ – the evaporation coefficient of the pheromone.

The evaporation coefficient takes a value from 0 to 1. When $\rho = 1$ then the pheromone evaporates completely after each iteration. Therefore, the more ants move along the path, the more attractive it becomes to subsequent ants. This affects the probability that the next ant leaving the nest will choose the path.

In the "classic" approach, ACO finds the shortest route. In the issue under consideration, the length criterion alone is insufficient. Therefore, the authors modified the algorithm to be able to take into account more parameters that will make the paths easier or more difficult. As a result, the algorithm counts the effort that ants have to put into traversing the routes. MACO is based on the effort matrix:

$$E = \begin{bmatrix} E_{11} & \cdots & E_{1j} \\ \vdots & \ddots & \vdots \\ E_{i1} & \cdots & E_{ij} \end{bmatrix} \tag{2.5}$$

This matrix is square and symmetric. All modifications will be made to the E_{ij} coefficients of the matrix E. The coefficient E_{ij} determines the effort to cover the section *ij* according to the following formula:

$$E_{ij} = \frac{L_{ij}}{L_c} \cdot \left(1 - \frac{I_{ij}}{I_c}\right) \cdot \frac{1}{A_{ij}} \cdot \frac{S_{\max}}{S_c} \tag{2.6}$$

where: E_{ij} – the ant's effort between section *ij*, L_{ij} – the distance between section *ij*, L_c – the total length of route, I_{ij} – the approximate number of inhabitants located in the area of section *ij*, I_c – the total number of inhabitants located in the route area, A_{ij} – the attractiveness index, $S_{\max}$ – the maximum number of new areas with access to the rail network among all proposed routes, S_c – the total number of new areas with access to the railroad network.

A detailed description of Eq. (2.6) can be found in the author's previous paper [34]. In step one, single route proposals are evaluated. The routes are designed on the basis of traffic generators located in the city center. This is a factor that could potentially increase the attractiveness of the suburban rail network thus created. In addition, the routes should be designed so that it is possible to connect them to the existing rail infrastructure. Along the routes, the location of stations (usually located at traffic generator sites) is determined. Then determine the coefficients E_{ij} of the E matrix according to Eq. (2.6). The result is an effort matrix (E_n value) for each route. The authors implemented MACO in the Python programming language, into which the determined E matrices are input. The program determines the best route and provides the value of effort E. The resulting values allow you to proceed to step two of the evaluation. The algorithm works based on the following pseudocode:

Algorithm 1. The way of finding the best route using MACO	
Input:	effort matrix E
2:	number of iteration N
3:	number of ants M
4:	number of nodes (station) n
5:	evaporation rate ρ
1:	**For** $i = 1$ to N
2:	**For** $k = 1$ to M
3:	Repeat until k-ant has completed aroute
4:	Select the nodes n to be visited next
5:	With probability p_{ij}^{k} given by E
6:	Calculate the effort for the route
7:	Update the pheromone (evaporation) according to ρ
Output:	the best route, E_n

2.2. Step two

Step two allows the evaluation of variants consisting of more than one route. This makes it possible to examine the issue more accurately, adding new evaluation criteria. In addition, it is possible to check more thoroughly which combination of routes would work better to create a suburban railroad. The evaluation is based on the following formula:

$$M_m = \sum_n \left(E_n \cdot \frac{t_n}{t_{A,n}} \right) \cdot e^{\frac{L_m}{L_{\max}}} \tag{2.7}$$

where: M_m – a modified effort of artificial ants for m-variant, E_n – the effort calculated from Python for the n-route in step one; t_n – the crossing time of the n-route; $t_{A,n}$ – a travel time for a chosen n-route by alternative means of public transport; L_m – the sum of the route lengths for m-variant; $L_{\max}$ – the sum of the longest combination of proposed routes in the paper.

The evaluation begins by combining the prepared route proposals into variants. Although it is also possible for a variant to be a single route. The variants are prepared so that a suburban rail network can be established in the future. For each route, the time taken to travel through the tunnel and the time taken to travel the route by alternative public transport are counted separately. The value of t_n is calculated on the basis of the graphical timetable taking into account acceleration, deceleration and stopping of trains and the assumption that trains can run in the tunnel at a maximum speed of 60 km/h. The $t_{A,n}$ value is determined from the timetable available on the operator's website (MPK Wrocław). The value of $e^{L_m/L_{\max}}$ allows to take into account the cost of realizing the proposed variants. The authors assumed that the cost increases exponentially. The cost is compared against the longest combination of proposed routes. Therefore, the value depends on the ratio of L_m to $L_{\max}$. The higher value of L_m, the greater the modified effort. For the longest combination of routes, the ratio of L_m to $L_{\max}$ is 1, and this is the highest possible value. For the other variants, the obtained value of $e^{L_m/L_{\max}}$ is lower, depending on the sum of route lengths. The final result is a modified value of the effort the artificial ants have to put in to cover the routes in a given variant. The obtained values for evaluating the variants will be able to compare among themselves and see which proposal is the best. The smaller the value of M, the better is of the proposed variants.

3. Application example

The research is based on the example of the city of Wroclaw (Poland). The city is located in Lower Silesia in south-western Poland. It has a population of about 675,000 and the entire agglomeration has more than 1 million inhabitants. The Wroclaw Railway Junction (WRJ) is very well developed. Railroad lines propagate in ten directions. Along with a bypass for cargo trains and other railroads, the WRJ is one of the largest railroad junctions in Poland. Although the city is large and has a dense rail network, it does not have a suburban railroad. Also a problem is the lack of rail accessibility in the center and the limited capacity of the current cross-city section. The main WRJ's problem is the lack of railroads in the downtown area. On the border of the downtown area there are three railroad stations such as:

– Main Railway Station (MRS) – the most important railroad station in Wroclaw. The main interchange point in the city,
– Nadodrze Railway Station (NRS) – a significant railroad station located in the northern part of the city center,
– Świebodzki Railway Station (SRS) – is currently out of use, but there are plans to reactivate rail traffic. It is located closest to the city center.

Increasing rail accessibility in the center can significantly enhance the demand for rail service in the city and metropolitan area. It is good to create a rapid connection between stations, additionally including the city center in the network. Such a solution will enable the creation of a coherent WRJ and offers the potential for the creation of an efficient suburban rail network. To make this possible, new routes are needed, located in the city center. The Authors propose and evaluate five routes indicated in Fig. 2. In the figure, the black line shows the current state of the WRJ, the dashed line shows the sections planned for construction and the spots indicate the location of the proposed new stations. Due to the dense development in the center of the city, the only option is to build a tunnel. The proposed routes will form the core of the future suburban railroad. Therefore, a thorough analysis of the issue is important, and we used a two-step evaluation of the proposed variants.

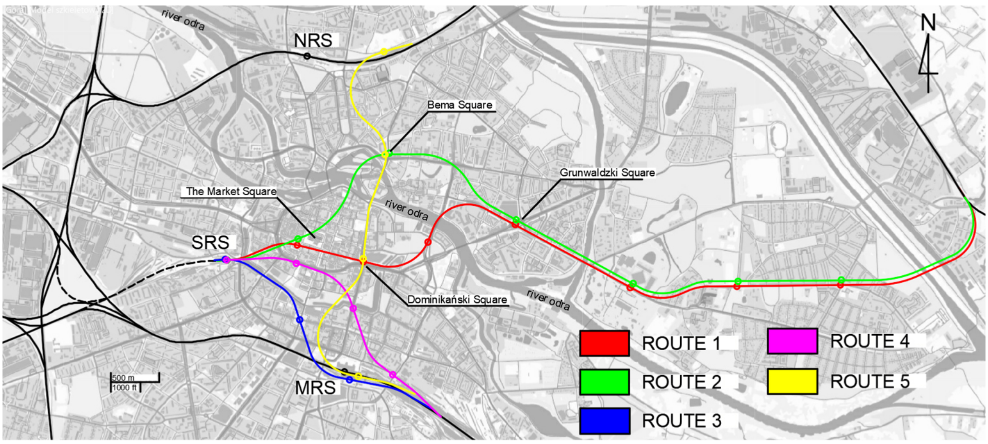

Fig. 2. Proposed routes. Marking: MRS – Main Railway Station, NRS – Nadodrze Railway Station, SRS – Świebodzki Railway Station

3.1. Step one

In step one, route proposals are evaluated. The authors in the previous paper [34] proposed routes based on points in the center that generate a lot of people traffic such as interchanges, universities, train and bus stations, business and service centres. Table 1 shows the most important information regarding each route proposal. For each route, a marker has been applied according to the route number, i.e. for route one the marker is R1 and so on.

An effort matrix E is then determined based on Eq. (2.6) and input into Python. The program calculates the effort required to cover each route. This is the element that completes step one.

Table 1. Summary of route proposals in step one

Route number	**Route marker**	**Route length [m]**	**Number of stations (S_c)**	**Number of inhabitants located in the tunnel area* (I_c)**	**Effort (from Python) (E)**
1	R1	8,382	9	43,000	30.2
2	R2	9,262	8	44,000	33.9
3	R3	1,927	3	17,000	26.2
4	R4	2,447	4	19,000	30.6
5	R5	3,886	4	20,000	37.3

* The estimated number of inhabitants living in the area near the station is determined on the basis of GIS data for the city of Wrocław. A map of the city shows the population density of the individual city regions. In this paper, the station area is assumed to be a circle with a radius of 300 m.

3.2. Step two

In step two, the authors propose to create variants. Variants one through five consist of one route, analyzed in step one. Variant six consists of routes one and three. Variant seven consists of route two and route three. Variant eight consists of route two and route four. Variant nine consists of routes one and five. Variant ten consists of route two and route five. Variant eleven consists of route one, route three and route five.

Other route combinations are also possible. The authors consider that the variants proposed in the paper could have the biggest impact on the functioning of the entire rail network. The details of the variants are shown in Table 2. Based on Eq. (2.7) and the data in Table 1, the rating of the proposed variants is calculated.

Table 2. Summary of route proposals in step two

Variant number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Routes marker	**R1**	**R2**	**R3**	**R4**	**R5**	**R1+R3**	**R2+R3**	**R2+R4**	**R1+R5**	**R2+R5**	**R1+R3+R5**
L_m [m]	8,382	9,262	1,927	2,447	3,886	10,309	11,189	11,709	12,268	13,148	14,195
t_n [min]	17	15	3	4	6	N/A	N/A	N/A	N/A	N/A	N/A
t_A [min]	31	39	6	10	16	N/A	N/A	N/A	N/A	N/A	N/A

3.3. Results

Table 3 summarizes the final evaluation values for the proposed variants. The lower the value a variant obtains, the better it will be as an addition to the WRJ. In addition, the lower the value obtained, the greater the chances of creating an efficient suburban rail network.

Table 3. The final evaluation of variants

Variant number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
$\frac{t_n}{t_{A,n}}$	0.55	0.38	0.50	0.40	0.37	N/A	N/A	N/A	N/A	N/A	N/A
M_m	29.89	25.04	15.00	14.54	18.39	61.32	57.49	57.67	72.50	68.24	118.65

The lowest value is obtained for variant four and is 14.54. The elements of this value include: the effort the artificial ants had to put in to cover route two $E_4 = 30.6$ (from Python); the time it needed to cover route two $t_4 = 15$ min; the time to cover route two by alternative public transport $t_{4,a} = 39$ min; the sum of the route lengths for variant four $L_4 = 2,447$ m; the sum of the longest combination of proposed routes in the paper $L_{\max} = 14,195$ m. The highest value is obtained for variant eleven and is 118.65. The method of calculating the highest value is the same as for the lowest value. The only difference is the inclusion of more routes.

In addition, Table 3 shows the $t_n/t_{A,n}$ ratio. Based on it, it is possible to determine the time savings that can be achieved in the development of the proposed route. The $t_n/t_{A,n}$ ratio applies only to single routes. Therefore, these values are shown only for variants one to five. The lower the value of $t_n/t_{A,n}$, the greater the time savings, and thus the better in the context of creating a suburban rail Network.

4. Alternative method

The authors present an alternative solution to the problem under consideration. Using an algorithm based on multi-criteria analysis, it is possible to evaluate the proposed routes. The criteria considered, will be the same factors as in the method using MACO, which are:

- Route length (data in Table 1, column 3),
- Number of stations (data in Table 1, column 4),
- Number of inhabitants located in the tunnel area (data in Table 1, column 5),
- The ratio of the crossing time of the route to the travel time for a chosen route by alternative means of public transport (data in Table 3, column 2).

In order to be able to use the data used in the MACO method, the analysis is reduced to the evaluation of single routes rather than variants. The algorithm is based on a point and weight system. Each factor will be scored separately on a scale of 1 to 10, with 1 being the least beneficial value and 10 being the most beneficial value, in terms of the construction and later operation of the route. Mid-points have been calculated in proportion to the best and worst value. In order to obtain more accurate results, the individual criteria will be weighted, the sum of which is one. The algorithm works as follows:

Algorithm 2. The way of finding the best route using multi-criteria analysis	
Input:	list of routes $(R_1, R_2, \ldots, R_n)$
2:	list of factors $(F_1, F_2, \ldots, F_n)$
3:	cases of weight $(C_1, C_2, \ldots, C_i)$
4:	**For** W_i **in** cases of weight
5:	**For** R_i **in** list of routes
6:	**For** F_i, C_i **in** (list of factors, weights)
7:	$F_i = (v_1, v_2, \ldots, v_i)$
8:	$C_i = (w_1, w_2, \ldots, w_i)$
9:	calculate the intermediate V-values
10:	calculate the final value
11:	return
Output:	Overview of variants

Table 4 shows the points obtained for each factor without taking the weights into account. Below the table the weights, for each factor, are indicated. The authors consider five cases. In the first case, the weights have the same value. In the other cases, the values of the weights are different, with one of the factors being the leading one and assigned the highest weight. The values of the weights are taken in such a way that each factor has any influence on the final result.

The final values are calculated using the following formula:

$$V = \sum_{\text{i=1}}^{\text{n}} v_i \cdot w_i \tag{4.1}$$

where: V – the weighted final value obtained for each route, n – the number of criteria analyzed, v_i – the points obtained for each factor, w_i – the weight of the factor.

The final values obtained are summarized in Table 5. The higher the value obtained for a route, the better. This is the opposite approach to the method using MACO, where the higher the value the worse.

In each of the cases considered, route one is the best and route five the worst. It can be initially concluded that the results obtained are correlated with the length of the route. However, route length is not the crucial determinant, as the worst result is obtained by the route that is not the shortest. The correlation that the longer the route, the more stations, and the more stations the greater the passenger potential and the greater the accessibility, proved to be important. The application of different weighting cases did not result in a significant change in the results obtained. It would have been necessary to use unequal weighting values in order to be able to

Table 4. Point Scored (without weights)

Route marker	**Factors**			
	Route length	**Number of stations**	**Number of inhabitants located in the tunnel area**	$t_n/t_{A,n}$
R1	2.08	10.0	9.67	10.0
R2	1.00	8.50	10.0	1.50
R3	10.0	1.00	1.00	7.50
R4	9.36	2.50	1.67	2.50
R5	7.60	2.50	2.00	1.00
Weight (case 1)	0.25	0.25	0.25	0.25
Weight (case 2)	0.40	0.25	0.20	0.15
Weight (case 3)	0.15	0.40	0.25	0.20
Weight (case 4)	0.20	0.15	0.40	0.25
Weight (case 5)	0.25	0.20	0.15	0.40

Table 5. Results of the mulit – criteria analysis

Route marker	***V* for case 1**	***V* for case 2**	***V* for case 3**	***V* for case 4**	***V* for case 5**
R1	7.94	6.77	8.73	8.28	7.97
R2	5.25	4.75	6.35	5.85	4.05
R3	4.88	5.58	3.65	4.43	5.85
R4	4.01	5.08	3.32	3.54	4.09
R5	3.28	4.22	2.84	2.95	3.10

balance the inequality related to route length. According to the authors, such a solution would have produced different solutions, but the results obtained would not have been meaningful. The method presented here shows that the weighting system is crucial in multi-criteria analysis.

5. Discussion

The paper presents an novel tool to effectively support the transport infrastructure planning process. To this end, the authors propose a two-stage evaluation method based on MACO. In step one, single route proposals are evaluated using MACO. Five routes are evaluated. Using the Python programming language, the effort the artificial ants had to put in to cover each route is determined. In step two, the proposed routes combined to form variants. Using the new evaluation criteria, step two determines the modified effort that the artificial ants need to put into covering the routes in a chosen variant. The criteria analyzed in step two are the travel time of the new route, the travel time on the proposed route by alternative public transportation and the cost of realizing the variant determined by the length of the routes. Eleven variants are proposed. A two-step analysis of the issue allowed for the inclusion of more than one route within a single variant. This allows for a more in-depth evaluation of the proposed variants and thus better adaptation of the WRJ to transportation needs. In addition, the authors present an alternative approach to the problem under consideration using multi-criteria analysis and a weighting system in five cases.

The final results show that the proposed variants can be divided into three groups depending on the number of routes. The lowest M values have variants one through five, that is, consisting of one route. Among them, variant four has the best result with a value of 14.54. Variant three has a similar value. Both variants are the shortest among those considered in the paper. These are the routes that connect the MRS and SRS. The next group is variants six through ten with two routes. Among them, variant seven has the best score with a value of 57.49. Variant eight also has a similar score. They consist of a route connecting the MRS and the SRS and a long east-west second route. The worst result has the eleventh variant with a value of 118.65. It consists of three routes and is the most extensive.

An algorithm based on multi-criteria analysis is a method that allows the best option to be selected, but it has its restrictions. The main problem with this method is the way in which weights are assigned to the specific factors. Frequently, the weights are determined subjectively by the authors, based on their knowledge and experience. This allows the data obtained to be freely manipulated based solely on the weights. This means that this type of method may not show effective solutions. The method presented by the authors using MACO is less susceptible to manipulation of the results, as it is based on an algorithm into which deterministic data are input.

6. Conclusions

The research methodology used in the study made it possible to evaluate route variant proposals, which are components of the entire transportation network. With the results obtained, it is possible to compare the variants and determine the differences between them. The proposed method can effectively support the process of designing new transport infrastructure.

The presented methodology contains novel elements and their implementation to specific infrastructure elements. Due to its novelty, it is difficult to compare the presented method with other evaluation methods, and the use of multi-criteria analysis allowed only a partial examination of the problem, considering only single routes. However, similar use of heuristic methods including ACO indicates that the proposed method can be used for transportation issues. Examples of its application are commented on in the initial part of the paper.

The results indicate that there are issues that need further consideration in future research. A problem with the proposed method is how it compares the results obtained with another algorithm, due to the unusual approach to the problem. In addition, a concrete number of variants are evaluated, and there are more possible routing alternatives. This is due to the fact that the authors in the paper evaluated the proposals that would best complement the current transport network. Therefore, future research should consider finding a method (algorithm) to compare the considered tool with another, in order to better compare the results obtained. It is also worth exploring more variants. It could be considered whether the evaluation criteria and their number are sufficient to select the optimal variant, and whether the evaluation criteria should have their own scales to distinguish more strongly between the criteria in terms of their importance for the entire transport network.

References

[1] E. Cascetta, *Transportation systems engineering: theory and methods*. Springer Science & Business Media, 2001, doi: 10.1007/978-1-4757-6873-2.

[2] H. Zhang, G. Lu, Y. Lei, G. Zhang, and I. Niyitanga, "A hybrid framework for synchronized passenger and train traffic simulation in an urban rail transit network", *International Journal of Rail Transportation*, vol. 11, no. 6, pp. 912–941, 2023, doi: 10.1080/23248378.2022.2109522.

[3] R. Bozzo, M. Canepa, C. Carnevali, R. Genova, and G. Priano, "Method for analysis and comparison in planning urban surface transport systems", *Sustainable City*, vol. 155, pp. 931-942, 2012, doi: 10.2495/SC120782.

[4] H. Orth, A. Nash, and U. Weidmann, "Level-Based Approach to Public Transport Network Planning", *Transportation Research Record*, vol. 2537, no. 1, pp. 1–12, 2015, doi: 10.3141/2537-01.

[5] G. Koroń and R. Żochowska, "Problems of Quality of Public Transportation Systems in Smart Cities-Smoothness and Disruptions in Urban Traffic", in *Modelling of the Interaction of the Different Vehicles and Various Transport Modes*. Springer, 2020, pp. 383–414, doi: 10.1007/978-3-030-11512-8_9.

[6] X. He, Z. Cao, S. Zhang, S. Liang, Y. Zhang, T. Ji, and Q. Shi, "Coordination Investigation of the Economic, Social and Environmental Benefits of Urban Public Transport Infrastructure in 13 Cities, Jiangsu Province, China", *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, art. no. 6809, 2020, doi: 10.3390/ijerph17186809.

[7] M. Kruszyna, "Investment challenges pertaining to the achievement of the goals of the Mobility Policy based on the analysis of the results of traffic surveys in Wroclaw", *Archives of Civil Engineering*, vol. 67, no. 3, pp. 505–523, 2021, doi: 10.24425/ACE.2021.138068.

[8] M. Kruszyna and J. Makuch, "Mobility Nodes as an Extension of the Idea of Transfer Nodes - Solutions for Smaller Rail Stations with an Example from Poland", *Sustainability*, vol. 15, no. 3, art. no. 2106, 2023, doi: 10.3390/su15032106.

[9] M. Owais, A.S. Ahmed, G.S. Moussa, and A.A. Khalil, "Design scheme of multiple-subway lines for minimizing passengers transfers in mega-cities transit networks", *International Journal of Rail Transportation*, vol. 9, no. 6, pp. 540–563, 2021, doi: 10.1080/23248378.2020.1846632.

[10] C.L. Mumford, "New Heuristic and Evolutionary Operators for the Multi-Objective Urban Transit Routing Problem", in *IEEE Congress on Evolutionary Computation, 20-23 June 2013, Cancún, México.* IEEE, 2013, doi: 10.1109/CEC.2013.6557668.

[11] S.A. Bagloee and A. Ceder, "Transit-network design methodology for actual-size road networks", *Transportation Research Part B*, vol. 45, no. 10, pp. 1787–1804, 2011, doi: 10.1016/j.trb.2011.07.005.

[12] Q. Wu, C. Cole, and T. McSweeney, "Applications of particle swarm optimization in the railway domain", *International Journal of Rail Transportation*, vol. 4, no. 3, pp. 167–190, 2016, doi: 10.1080/23248378.2016.1179599.

[13] Y. Zhang, S. Wang, and G. Ji, "A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications", *Mathematical Problems in Engineering*, vol. 2015, art. no 31256, 2015, doi: 10.1155/2015/931256.

[14] H. Khudov, V. Koval, I. Khizhnyak, Y. Bridnia, V. Chepurnyi, S. Prykhodko, O. Oleksenko, S. Glukhov, and V. Savran, "The Method of Transport Logistics Problem Solving by the MAX-MIN ACO Algorithm", *International Journal of Emerging Technology and Advanced Engineering*, vol. 12, no. 7, pp. 108–119, 2022, doi: 10.46338/ijetae0722_12.

[15] Z. Zukhiri and I. V. Paputungan, "A hybrid optimization algorithm based on genetic algorithm and ant colony optimization", *International Journal of Artificial Intelligence & Applications*, vol. 4, no. 5, 2013, doi: 10.5121/ijaia.2013.4505.

[16] B. Hickish, D.I. Fletcher, and R.F. Harrison, "Investigating Bayesian Optimization for rail network optimization", *International Journal of Rail Transportation*, vol. 8, no. 4, pp. 307–323, 2020, doi: 10.1080/23248378.2019.1669500.

[17] R. Tang, L. De Donato, N. Bes¢inović, F. Flammini, R.M.P. Goverde, Z. Lin, R. Liu, T. Tang, V. Vittorini, and Z. Wang, "A literature review of Artificial Intelligence applications in railway systems", *Transportation Research Part C*, vol. 140, pp. 1–25, 2022, doi: 10.1016/j.trc.2022.103679.

[18] C. Blum, "Ant colony optimization: Introduction and recent trends", *Physics of Life Reviews,* vol. 2, no. 4, pp. 353–373, 2005, doi: 10.1016/j.plrev.2005.10.001.

[19] R.M. Hasany and Y. Shafahi, "Ant colony optimisation for finding the optimal railroad path", *Transport*, vol. 170, no. 4, pp. 218–230, 2017, doi: 10.1680/jtran.15.00038.

[20] J.E. Bell and P.R. McMullen, "Ant colony optimization techniques for the vehicle routing problem", *Advanced Engineering Informatics*, vol. 18, no. 1, pp. 41–48, 2004, doi: 10.1016/j.aei.2004.07.001.

[21] B. Alt and U. Weidmann, "A stochastic multiple area approach for public transport network design", *Public Transport*, vol. 3, pp. 65–87, 2011, doi: 10.1007/s12469-011-0042-0.

[22] M. Pang, X. Wang, and L. Ma, "Transit route planning for megacities based on demand density of complex networks", *Promet – Traffic & Transportation*, vol. 34, no. 1, pp. 13–23, 2022, doi: 10.7307/ptt.v34i1.3752.

[23] Z. Yang, B. Yu, and C. Cheng, "A Parallel Ant Colony Algorithm for Bus Network Optimization", *Computer-Aided Civil and Infrastructure Engineering*, vol. 22, pp. 44–55, 2007, doi: 10.1111/j.1467-8667.2006.00469.x.

[24] G. Katona, J. Juhász, and B. Lénárt, "Travel habit based multimodal route planning", *Transportation Research Procedia*, vol. 27, pp. 301–308, 2017, doi: 10.1016/j.trpro.2017.12.121.

[25] S.K. Sahana, A. Jain, and P.K. Mahanti, "Ant Colony Optimization for Train Scheduling: An Analysis", *International Journal of Intelligent Systems and Applications*, vol. 6, no. 2, pp. 29–36, 2014, doi: 10.5815/ijisa.2014.02.04.

[26] A. Mishra, N. Kumar, and S. Kharb, "Priority Based Train Scheduling Method Using ACO in Indian Railway Perspective", *Institute of Physic Conference Series: Materials Science and Engineering*, vol. 998, art. no. 012016, 2020, doi: 10.1088/1757-899X/998/1/012016.

[27] Z. Li and J. Huang, "How to Mitigate Traffic Congestion Based on Improved Ant Colony Algorithm: A Case Study of a Congested Old Area of a Metropolis", *Sustainability*, vol. 11, no. 4, pp. 1–15, 2019, doi: 10.3390/su11041140.

[28] Y. Bin, Y. Zhong-Zhen, and Y. Baozhen, "An improved ant colony optimization for vehicle routing problem", *European Journal of Operational Research*, vol. 196, no. 1, pp. 171–176, 2009, doi: 10.1016/j.ejor.2008.02.028.

[29] L. Yongqiang, C. Qing, and X. Huagang, "An Improved Ant Colony Algorithm for the Time-Dependent Vehicle Routing Problem", in *International Conference on Logistics Engineering and Intelligent Transportation Systems*. IEEE, 2010, doi: 10.1109/LEITS.2010.5665028.

[30] M. Yousefikhoshbakht, F. Didehvar, F. Rahmati, and Z. Ahmed, "Fixed fleet open vehicle routing problem: Mathematical model and a modified ant colony optimization", *Bulletin of the Polish Academy of Sciences Technical Sciences*, vol. 72, no. 1, 2024, doi: 10.24425/bpasts.2023.148253.

[31] W. Liu, "Route Optimization for Last-Mile Distribution of Rural E-Commerce Logistics Based on Ant Colony Optimization", *IEEE Access*, vol. 8, pp. 12179–12187, 2020, doi: 10.1109/ACCESS.2020.2964328.

[32] W. Zhang, X. Gong, G. Han, and Y. Zhao, "An Improved Ant Colony Algorithm for Path Planning in One Scenic Area With Many Spots", *IEEE Access*, vol. 5, pp. 13260–13269, 2017, doi: 10.1109/ACCESS.2017.2723892.

[33] Y. Wei, N. Jiang, Z. Li, D. Zheng, M. Chen, and M. Zhang, "An Improved Ant Colony Algorithm for Urban Bus Network Optimization Based on Existing Bus Routes", *International Journal of Geo-Information*, vol. 11, no. 5, art. no. 317, 2022, doi: 10.3390/ijgi11050317.

[34] M. Korzeń and M. Kruszyna, "Modified ant Colony Optimization as a Means for Evaluating the Variants of the City Railway Underground Section", *International Journal of Environmental Research and Public Health*, vol. 20, no. 6, art. no. 4960, 2023, doi: 10.3390/ijerph20064960.

[35] M. Dorigo and T. Stützle, "Ant Colony Optimization: Overview and Recent Advances", in *Handbook of Metaheuristics*, M. Gendreau and J.Y. Potvin, Eds. International Series in Operations Research & Management Science, vol. 146. Springer, 2010, pp. 227–263, doi: 10.1007/978-1-4419-1665-5_8.

Podejście do projektowania infrastruktury transportowej z wykorzystaniem dwuetapowej metody bazującej na zmodyfikowanym algorytmie mrówkowym

Słowa kluczowe: dwuetapowa ocena, infrastruktura transportowa, tunel kolejowy, transport zbiorowy, zmodyfikowany algorytm mrówkowy

Streszczenie:

Głównym celem pracy jest opracowanie narzędzia, które umożliwi efektywne wsparcie w procesie planowania infrastruktury transportowej głównie pod kątem transportu zbiorowego. Nowatorska metoda opiera się na zmodyfikowanym algorytmie mrówkowym i jest wykorzystywana do oceny proponowanych nowych odcinków infrastruktury. Ocenie mogą podlegać warianty składające się z jednej lub więcej tras, co stanowi duży atut proponowanego narzędzia. Autorzy proponują dwuetapową ocenę. W kroku pierwszym przy użyciu zmodyfikowanego algorytmu mrówkowego oceniane są pojedyncze trasy. W rezultacie dla każdej trasy uzyskuje się wysiłek, jaki wirtualne mrówki muszą włożyć na pokonanie jej. Wysiłek ten jest obliczany bazując na odległości, potencjału pasażerskiego, atrakcyjności obszarów oraz dostępności do sieci kolejowej. W kroku drugim proponowane trasy są łączone w warianty. Bazując na wartościach otrzymanych w kroku pierwszym, dla każdego wariantu wyliczana jest zmodyfikowana wartość wysiłku. W tym celu wykorzystuje się dodatkowe kryteria oceny związane z czasem przejazdu oraz kosztem realizacji. Studium przypadku zlokalizowane jest we Wrocławiu i dotyczy problemu utworzenia nowego odcinka średnicowego. Otrzymane wyniki pokazują użyteczność metody w ocenie wariantów tunelu kolejowego. Ważną kwestią jest również to, że wszystkie kryteria mają wpływ na ocenę końcową. Przedstawiona metodyka zawiera nowatorskie elementy i ich implementację do konkretnych elementów infrastruktury transportowej. Otrzymane wyniki zestawiono z algorytmem opartym na analizie wielokryterialnej. Wykazało to większą złożoność proponowanego narzędzia, a tym samym lepsze przeanalizowanie problemu.

Received: 2024-02-01, Revised: 2024-05-21