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The Effect of Candidate Routes Alignment over Transit Coverage in a Grid Network

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A B S T R A C T

The design of public transportation (transit) route networks involves identifying the most efficient configuration of routes in an urban setting so as to maximize an objective function, such as network coverage, within the available budget. This problem is generally addressed through two key stages: the generation of potential candidate routes to be selected and the subsequent selection of final routes. According to the literature, the "pool" of candidate routes in the first stage plays a critical role in determining the quality of the selected routes in the second stage. However, in certain network topologies, such as grid-structured networks, urban planners often prefer introducing candidate routes oriented horizontally (east-west) or vertically (south-north). The impact of restricting the candidate routes to exclusively horizontal and vertical routes has not been studied much in existing research. To address this gap, this study examines two scenarios: (1) unrestricted candidate routes and (2) candidate routes restricted to horizontal and vertical orientations. The results averaged for a 6×10 grid network suggest that adopting horizontally and vertically restricted candidate routes results in only a 2% reduction in network coverage compared to using unrestricted candidate routes.

1. Introduction and research background

Public transportation systems are recognized as an integral part of modern cities and serve as a cornerstone for sustainable urban development. Encouraging the use of public transit through the design of strategically efficient routes can help modern cities significantly reduce their fuel consumption, thereby mitigating greenhouse gas emissions and contributing to their environmental preservation. Furthermore, an affordable transit system improves the overall quality of urban life by minimizing travel times, conserving energy, and enhancing convenience for city inhabitants [1, 2]. Given these multifaceted benefits, public transportation has emerged as a recurrent and pivotal theme in transportation planning literature over recent decades.

The process of transit planning comprises a variety of decision-making problems, ranging from long-term decisions with decades-long implications to short-term operational choices made on a daily or weekly basis. Researchers have adopted a structured framework for this process by breaking it down into separate steps of route design, frequency setting, and vehicle/crew scheduling [3]. Among these steps, transit routes design is the most important part as it entails strategic decisions that substantially influence subsequent steps of the planning process [4]. As a result, a great deal of research has been dedicated to developing innovative methodologies and tools, only to identify transit routes configuration in recent decades [1, 2, 5].

The problem of transit route design is focused on determining the optimal configuration of public transportation routes within a city network, with the aim of optimizing a specified objective function. This must be achieved within a limited budget, which in turn, necessitates the efficient allocation of resources [4]. At its core, the problem of network design falls under the category of NP-hard problems, which are characterized by their intractable computational complexity [6]. In practice, this means that obtaining

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exact solutions (i.e., “global optimal” configurations in the search space of the problem) becomes impossible for large-scale networks due to the exponential growth in computational requirements. As a result, the research relies on non-exact solution methods, including heuristic or meta-heuristic algorithms, to address this problem effectively. These algorithms, designed to provide near-optimal solutions within a reasonable timeframe, have proven to be indispensable tools for tackling large transit route design problems in urban environments [7, 8].

The transit routes design problem is generally approached as a two-stage process: route generation followed by route selection. In the first stage, a comprehensive set of candidate routes is created, incorporating alternatives with varying shapes and lengths. In the second stage, the optimal routes configuration is identified by selecting from the generated pool, while maintaining budgetary constraints. Various aspects of this problem have been explored in the research background [9]. Numerous studies have proposed a variety of solution approaches, ranging from the development of innovative heuristic algorithms [8] to the application of metaheuristic algorithms, such as genetic algorithms [10, 11], ant colony optimization [12], and simulated annealing [13]. The objective functions considered in these studies often include maximizing transit ridership [14], network coverage [15], equity measures [16], or minimizing the number of transfers over transit routes [10], system costs [4], and environmental pollution [17].

In addition to the above contributions, other research efforts have focused on addressing demand-side variations, incorporating the multi-objective nature of the problem, and employing stochastic or robust optimization approaches [4, 10, 18]. Furthermore, the interaction between transit systems and other modes of transportation has emerged as another critical area of research [19]. Despite all these efforts, research in these areas remains ongoing, as the complexity and scope of route design pose a broad spectrum of problems for further exploration. For a more comprehensive review of the literature, the interested reader may consult recent review papers and the references cited therein [10, 20, 21].

Among other aspects of the transit routes network design problem, an interesting yet relatively underexplored area is the examination of characteristics associated with specific network structures, such as grid networks, and the implications of these characteristics for designing route configurations. Grid-structured networks are exemplified today by many modern cities such as Kyoto, Beijing, and many North American cities. Transit networks employing a grid structure, with routes oriented predominantly in east-west or north-south directions, offer several attributes that render them attractive to the research community of urban planning. These attributes include their structural simplicity and operational clarity, predictable scheduling and optimized transfer systems, ease of planning and maintenance, and cost-effectiveness—particularly when mass transit systems are involved [22]. Based on these features, few studies have incorporated assumptions such as fixed spacing between lines or uniform/centripetal demand profiles to derive theoretical models and analyses over such networks [22-24]. Though certain aspects of the problem, e.g., the effect of candidate routes orientations over the results obtained for route configurations, remain inadequately studied, highlighting the need for further research.

One critical question in the design of an affordable routes system in a grid network corresponds to the definition of the pool of candidate routes. Due to the aforementioned attributes of grid networks, in urban planning, there is a tendency to define candidate routes along east-west (horizontal) or north-south (vertical) orientations. Referred to as “restricted candidate routes,” these predefined orientations prompt the inquiry of how much relaxing this constraint—i.e., incorporating routes that are not necessarily horizontal or vertical, namely “unrestricted” candidate routes—may enhance the quality of the final routes configuration. To investigate this question, this study examines two scenarios: one employing unrestricted candidate routes and the other employing restricted candidate routes. The results are reported in terms of network coverage over a 60 (6×10) node grid network. Our findings suggest that, interestingly, the scenario of restricted candidate routes can achieve solutions with 98% of the quality attained by unrestricted candidate routes.

The remainder of this paper is structured as follows: A general description of the problem is presented in Section 2. The two scenarios of candidate routes and corresponding solution algorithms are introduced in Section 3. The results are presented and discussed in Section 4, followed by concluding remarks in Section 5.

2. Description of the problem

The process of designing transit route networks is traditionally approached in two sequential phases: (1) route generation, which involves creating a pool of candidate transit routes, and (2) route selection, which focuses on identifying an optimal subset of routes from the generated pool. Defining the pool of candidate routes, in the first stage of design, has a large impact on the resulting network [3, 5]. This impact, however, in grid-structured networks, has not been addressed much in the literature. To further explore this effect over grid transportation networks, this section starts by introducing a general formulation of the routes design problem. First, we introduce the concept of network coverage, which is later applied as the study's objective function.

2.1. The concept of network coverage

One of the commonly applied objective functions at the strategic level of urban planning and decision-making is network coverage [15, 18]. In a general perspective, coverage refers to the proportion of network users that are potentially served by the configuration of transit routes in the network. To calculate this measure, it is important to consider that factors such as route transfers within the network and extended travel times associated with transit services can significantly reduce the share of transit in competition with other modes of transportation, such as private cars. Research has interestingly shown that travelers may even opt for longer routes to avoid frequent transfers [24]. To address these behaviors, this study applies a penalty of 5 additional minutes of travel time for each route transfer. Furthermore, while direct transit trips are considered to provide 100% coverage, coefficients of

70% and 50% are assigned to trips involving one and two transfers, respectively. Finally, a coefficient based on travel-time values is adopted to incorporate additional travel times imposed by transit service as compared to private vehicles.

The process for calculating coverage, as influenced by the above penalties, is illustrated in Fig. 1. In this figure:

C: the set of all acceptable candidate transit routes,

S: the set of selected candidate transit routes to be added to the network,

$Cov(S)$: the amount of network coverage (in passenger units) after adopting S as a subset of candidate transit routes, $S \subseteq C$,

$N(S)$: the underlying transportation network by adopting S as the set of transit routes, $S \subseteq C$,

$demand(o, d)$: the amount of transit travel-demand from o to d, $(o, d) \in OD$,

OD: the set of all origin-destinations in the network,

$P(o, d, N(S))$: the shortest transit path from o to d, by considering transfer penalties in $N(S)$, $(o, d) \in OD$, $S \subseteq C$,

$Tr(o, d, N(S))$: the shortest transit travel-time from o to d, by considering transfer penalties in $N(S)$, $(o,d) \in OD$, $S \subseteq C$,

$Au(o, d)$: the shortest auto travel-time from o to d,

$n(o, d, N(S))$: the number of line-transfers in the path $P(o, d, N(S))$, $(o, d) \in OD$, $S \subseteq C$.

$Cov(S) = 0$;
For each $(o,d) \in OD$
  Calculate $P(o,d,N(S))$, $\mathrm{Tr}(o,d,N(S))$, $n(o,d,N(S))$ and $\mathrm{Au}(o,d)$;
  if $n(o,d) = 0$
    $Cov(S) = Cov(S) + 1.0\times \mathrm{Au}(o,d)/\mathrm{Tr}(o,d,N(S))\times demand(o,d)$;
  else if $n(o,d) = 1$
    $Cov(S) = Cov(S) + 0.7\times \mathrm{Au}(o,d)/\mathrm{Tr}(o,d,N(S))\times demand(o,d)$;
  else if $n(o,d) = 2$
    $Cov(S) = Cov(S) + 0.5\times \mathrm{Au}(o,d)/\mathrm{Tr}(o,d,N(S))\times demand(o,d)$;

Fig. 1. The process of calculating network coverage.

As can be observed in Fig. 2, the initial value of Cov(S) is set to zero. Subsequently, through iterations for each origin-destination (O-D) pair, such as (o, d), the auto shortest path, transit shortest path, and the number of transfers involved are determined. The travel demand associated with the O-D pair is then added to the cumulative value of Cov(S).

Fig. 2 illustrates the use of coefficients 1.0, 0.7, and 0.5 to account for the inconvenience caused by line transfers for travelers, reducing the value of covered demand accordingly. Additionally, travel-time penalties for transit users are addressed by employing a coefficient represented as Au(o, d)/Tr(o, d, N(S)).

At the end of the iterative process in Fig. 2, Cov(S) is calculated in terms of passenger units over the network. Note that the value of coverage can also be expressed in terms of the percentage of the total travel demand, simply by calculating the ratio of the "covered" passengers to the total travel demand.

2.2. Problem formulation

We assume that the travel demand between origin-destination (O-D) pairs remains constant throughout the analysis period. To provide a generalized formulation of the problem, let us define:

L: an upper bound for the maximum length of all selected transit routes (previously defined) with regard to the budget constraint

K: the total number of candidate routes in the set C

l_k: the length of the k^{th} candidate route, $1 \le k \le K$

$b_k(S)$: a binary variable which is 1 if the k^{th} candidate route is a member of set S, and 0 otherwise, $1 \le k \le K$.

$$\max \quad Cov(S) \tag{1}$$

$$\text{s.t.} \quad S \subseteq C \tag{2}$$

$$\sum_{k=1}^{K} b_k(S)\, l_k \le L \tag{3}$$

In the above formulation, the objective function (1) intends to maximize the network's coverage by identifying an optimal subset of candidate routes, referred to as *S*. Meanwhile, constraint (2) states that the routes have to be selected from an "acceptable" pool of candidate routes. This acceptable pool will be further discussed later on in the next section. Constraint (3) also imposes a limit on the total length of selected transit routes, which must not exceed a specified value, *L*. This value is set based on the available budget for planning. It can be easily demonstrated that this formulation falls within the NP-hard category of problems and cannot be tackled by exact solution algorithms on a large scale.

3. Two scenarios for solving the problem

Given the problem definition in section 2.2, it is obvious that the set of candidate routes *C*, i.e., potential routes to select from, can affect the search space and therefore the quality of the routes configuration. In a general sense and from an operations research point of view, the larger the search space of *C*, the higher the quality of solutions to the problem. Nevertheless, when grid-structured transportation networks are involved, many urban planning authorities tend to restrict the candidate routes to horizontal (east-west) or vertical (north-south) routes and benefit from their orderly and reliable service. The pivotal question arising here is, to what extent can this restriction of candidate routes contribute to the reduction of network coverage?

To answer this question, we consider two scenarios in this study: scenario 1, in which candidate routes do not necessarily need to be horizontal or vertical, and scenario 2, in which candidate routes are restricted to horizontal or vertical routes. Fig. 2 provides a schematic overview of these two scenarios.

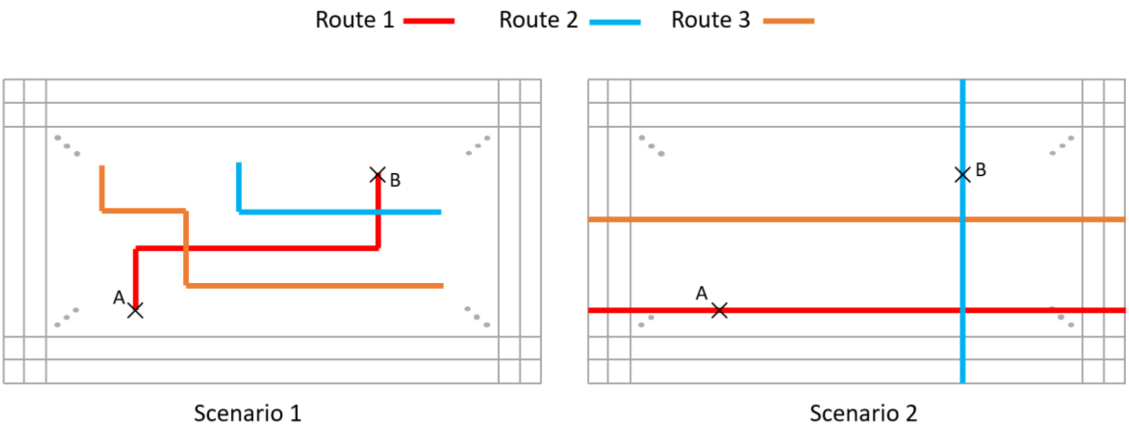


Fig. 2. Schematic overview of two scenarios for candidate transit routes.

To solve the problem in scenario 1, considering the intractable scale of the search space, a heuristic algorithm is introduced and applied in this study. Also, for scenario 2, an exact solution based on enumeration is exploited.

3.1. Scenario 1: Unrestricted candidate routes

In this scenario, the search space of the problem is extremely large even for medium-sized examples. As a result, a heuristic algorithm is presented in this section, which can be categorized as a constructive algorithm. The algorithm builds upon the idea of connecting the most promising nodes of the network using transit routes configuration. Prior to algorithm presentation, let us define *V* as the set of network nodes and d_{IJ} as the amount of travel demand from node *I* to node *J*, *I* and *J* ∈*V*. Based on these definitions, a measure of a node's importance, namely Level of Activity (LoA), is adopted for nodes of the network, as follows:

$$\mathrm{LoA}(N) = \sum_{I\in \mathrm{V}} d_{IN} + \sum_{J\in \mathrm{V}} d_{NJ} \qquad N \in V \tag{4}$$

According to (4), LoA(*N*) is the total amount of transit travelers ingoing to and outgoing from node *N*, *N* ∈*V*. It is obvious that nodes with higher values of LoA(*N*), while included in the transit routes configuration, are more likely to increase the overall coverage in the network. To present the solution algorithm, let us further define:

S: Set of selected candidate routes to be added to the network,

l(*A*, *B*): the length of the transit route between nodes *A* and *B*, and

l_{min}, l_{max}: standard values for minimum and maximum lengths for a transit route, respectively.

Based on the above definitions, Fig. 3 presents the proposed algorithm to solve the problem in scenario 1.

The algorithm in Fig. 3 starts by initialization and reading input data (steps 0 and 1). Prior to starting iterations (steps 3 to 6), the algorithm calculates the level of importance (namely LoA measure) for all nodes of the network (step 2). In the course of its iterations, in a greedy fashion, the algorithm picks up the two nodes *A* and *B* (e.g. the nodes depicted in Fig. 2) with maximum LoA from the set of nodes *V* (steps 3 and 4) and tries to connect them by introducing a direct shortest-path route to the set of transit routes (steps 5 and 6). The iterations will proceed until the algorithm fails to add more candidate routes within the available budget (step 6).

3.2. Scenario 2: Restricted (horizontal/vertical) candidate routes

In this scenario, the selection among candidate routes is restricted to only horizontal (east-west) and vertical (north-south) routes in the network. For example, for a grid network of n×m size, the number of candidate routes is limited to (n + m) routes, consisting of n horizontal and m vertical routes. Given the search space, which is now much smaller than that of scenario 1, problems of small-to-medium scale can now be solved using exact solution algorithms or even enumeration methods.

Let us define a dominant solution as a selection of candidate routes to which no further candidate route can be added while holding the budget constraint. Based on the definition of coverage in this study, the global optimal (i.e., exact) solution of the problem in scenario 2 can be found within the search space of dominant solutions. It is not difficult to prove this lemma in the sense that the addition of new candidate routes to a grid network will not lead to a decline in the value of coverage (as defined earlier in Fig. 3).

Step 0: Read the input data including transportation network, demand matrix, and budget level.

Step 1: $S \leftarrow \{\}$

Step 2: For each node of the network, N, $N \in V$, calculate LoA(N).

Step 3: remove from V the node $A = \underset{N \in V}{\text{Argmax}} \{ \text{LoA}(N) \}$

Step 4: Remove from V the node $B = \underset{N \in V}{\text{Argmax}} \{ \text{LoA}(N) \mid l_{min} \leq l(A,B) \leq l_{max} \}$

Step 5: Calculate the shortest path between A and B, namely R.

Step 6: If the level of budget allows, add R to the S, and go to step 3;
Otherwise, print the set of selected routes, S, in the output and finish.

Fig. 3. Heuristic algorithm to solve the problem in scenario 1.

Therefore, to solve the problem in scenario 2, one can simply perform an enumeration over dominant solutions of the problem and achieve the best solution obtained as the global optimal solution.

4. Results

To evaluate the results derived from the two introduced scenarios, the algorithms presented in the previous section are implemented using the Python programming language. A medium-sized grid network consisting of 60 (6×10) nodes is considered to run the programs. A general representation of this network is depicted in Fig. 4, where it is assumed that each block has a length and width of 2.2 km and 2 km, respectively, and the maximum length of public transit routes due to the budget constraint (i.e. the value for L in (3) in problem formulation) is constrained to 100 km. Additionally, it is assumed that travel demand values follow a uniform random distribution, and to report the results, 30 independent demand matrices are taken into consideration. Table 1 illustrates the coverage values obtained for each of the two scenarios.

According to the results in Table 1, after running the programs on 30 random demand matrices, the average coverage values obtained for scenarios 1 and 2 are 14.2% and 13.9%, respectively. These findings suggest that, despite restricting public transit lines to horizontal and vertical routes, it is still possible to achieve results with an average quality of 98% (i.e., 100 × 13.9/14.2%) compared to the unrestricted transit routes scenario.

The relatively small 2% difference between the two defined scenarios can be significant from an urban planning perspective. As mentioned in Section 1, numerous criteria other than coverage are involved in the urban design of cities. These criteria may justify such a reduction in coverage when adopting multi-objective planning approaches. As an example of the results obtained for both scenarios, Fig. 5 illustrates the route configurations for demand matrix 6 in Table 1. In this figure, (a) and (b) correspond to scenarios 1 and 2, respectively, where the coverage values of 14.22% and 13.89% are achieved.

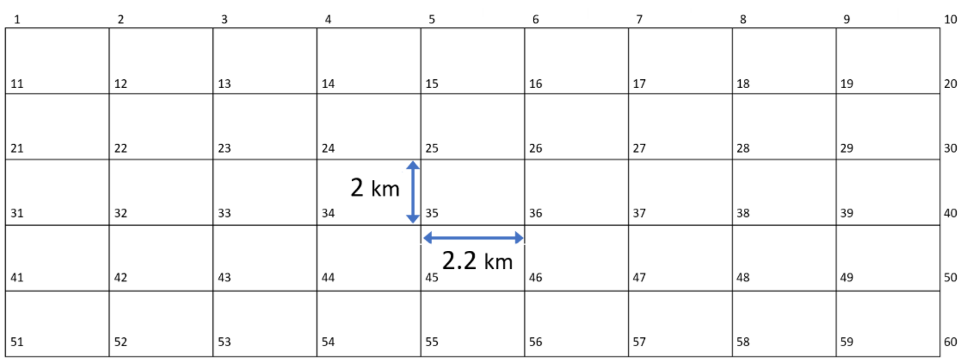


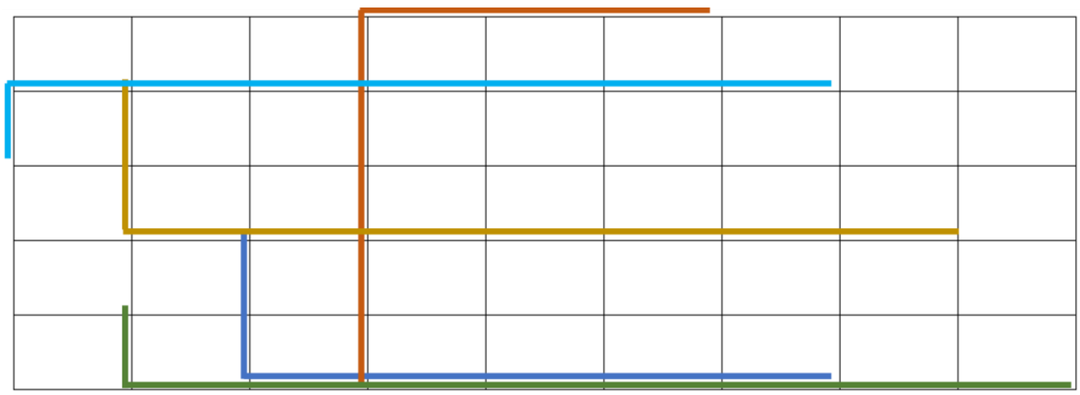
Fig. 4. 6×10 grid network used in this study.

5. Concluding remarks

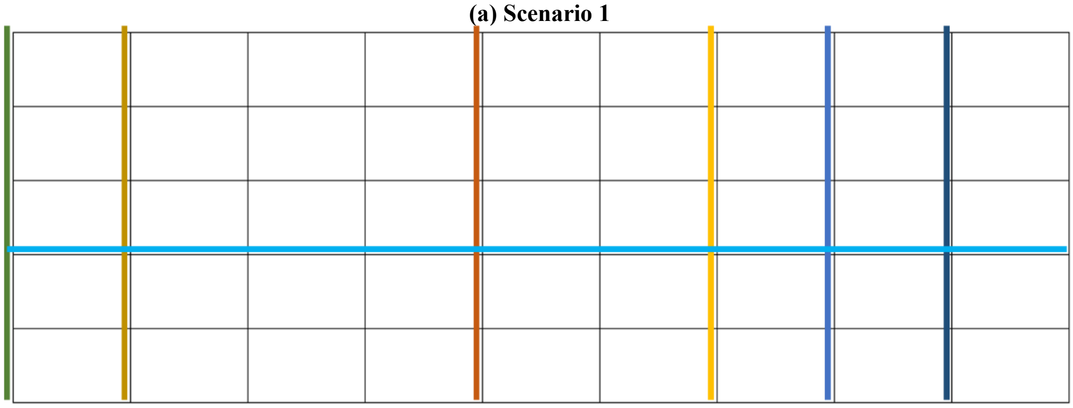
In this paper, the problem of transit routes configuration for grid networks was studied for the structure of its candidate routes. The paper aimed to answer this question: To what extent does restricting the search space of candidate routes to horizontal or vertical routes reduce the quality of the results in terms of network coverage?

Table 1. Results obtained for scenarios 1 and 2 over 30 random demand matrices.

Demand Matrix	Coverage (%)		Demand Matrix	Coverage (%)	
	Scenario 1	Scenario 2		Scenario 1	Scenario 2
1	11.9	13.5	16	16.3	13.8
2	14.8	13.6	17	9.5	13.9
3	15.7	13.6	18	13.2	13.5
4	18.3	13.7	19	11.7	13.9
5	15.2	14.0	20	13.1	13.8
6	14.2	13.9	21	12.3	13.9
7	13.8	13.7	22	17.0	13.6
8	15.9	13.9	23	12.7	13.7
9	16.5	13.9	24	11.0	13.5
10	15.7	13.5	25	15.3	13.9
11	14.6	13.8	26	16.5	13.7
12	15.4	13.7	27	10.6	13.8
13	17.2	13.9	28	16.6	13.9
14	11.4	13.9	29	12.9	13.5
15	11.8	14.0	30	13.6	16.7



(a) Scenario 1



(b) Scenario 2

Fig. 5. Results obtained for demand matrix 6.

Two scenarios were taken into account: (1) unrestricted candidate routes, in which there is no constraint for the shape of candidate routes, and (2) restricted (horizontal/vertical) candidate routes, in which only horizontal (east-west) or vertical (south-north) candidate routes can be selected. To examine the results, a medium-sized grid network of 60 nodes (6×10) was taken into account, and two algorithms corresponding to the scenarios were applied.

In the first scenario, a constructive algorithm was introduced that finds the most promising nodes of the network in terms of travel demand and tries to interconnect these nodes through route selection. In the second scenario, however, the search space is notably smaller and therefore an exact enumeration algorithm was applied to extract the global optimal solutions of the problem. The comparison between the two scenarios over 30 random travel demand matrices, interestingly, suggested that scenario 2 can lead to solutions with 98% coverage as compared to scenario 1. In other words, restricting the search space of candidate routes to horizontal/vertical routes, in this study, leads to only a 2% decline in the quality of the solutions.

To expand the findings of this study, several directions can be taken into account in future research. For example, more sophisticated and advanced algorithms for comparison can be investigated. Additionally, larger networks with other configurations can be considered for comparison between the two scenarios. Finally, exploring other travel demand patterns, e.g., centripetal demand matrices with single or multiple demand centers, can be an interesting topic for future research.

Statements & Declarations

Author contributions

Amirali Zarrinmehr: Conceptualization, Methodology, Supervision, Writing - Original Draft.

Mohammad Mehdi Ghasemi: Investigation, Visualization, Validation, Resources, Formal analysis.

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Data availability

The data presented in this study will be available on interested request from the corresponding author.

Declarations

The authors declare no conflict of interes.

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