ADBI Working Paper Series

A STATION LOCATION IDENTIFICATION MODEL FOR AN INTEGRATED INTEROPERABLE HIGH-SPEED RAIL SYSTEM

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No. 956
May 2019

Asian Development Bank Institute

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Suggested citation:

Roy, S. and A. Maji. 2019. A Station Location Identification Model for an Integrated Interoperable High-Speed Rail System. ADBI Working Paper 956. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/station-location-identification-model-high-speed-rail-system

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Abstract

Integrated interoperable rail systems facilitate high speed rail (HSR) train movement on conventional intercity lines, and vice versa. Hence, for such rail systems, it is preferred that HSR stations are located at existing intercity rail stations. However, all existing intercity stations may not satisfy the ridership potential and inter-station spacing required for HSR operation. Providing more stations increases access to intermediate locations, boosting ridership, but also increases overall travel time. On the contrary, fewer stations and stops reduce overall ridership of the HSR. This paper proposes a geographic information system-based interoperable HSR station location identification approach along existing intercity rail stations to identify suitable integrated interoperable HSR and intercity station locations. Avoiding environmentally sensitive land (such as wetlands, forests, etc.), and other requirements such as threshold inter-station distance and travel time between intended station locations and threshold population of the intended station region, are included as environmental, and corridor specific constraints, respectively. A heuristic approach is used to evaluate and obtain the candidate set of station locations that maximizes ridership and minimizes travel time, such that an integrated interoperable HSR and intercity corridor can be developed. The Mumbai–Ahmedabad conventional intercity corridor is used as a case study to demonstrate the efficacy of the proposed model by identifying possible HSR station locations.

Keywords: station location, location analysis, ridership, travel time, heuristic, intercity rail, corridor, interoperability, environment

JEL Classification: L92, R41, R58

Contents

1. INTRODUCTION AND BACKGROUND

High-speed railway (HSR) services are rail services that operate with considerably higher speeds than conventional trains. As per the European Union Directive 96/48/EC, HSR services operate at speeds greater than or equal to 250 km/h on specially built high-speed lines, and at speeds greater than or equal to 200 km/h on upgraded high-speed lines. The first areas that engaged in HSR projects were Japan and Europe countries such as France, Germany, and Italy. Major HSR projects are being implemented or developed currently in various countries in Asia and North and South America. The People's Republic of China (PRC) already has the longest HSR network in the world, with 19,000 km of HSR lines in service and another 12,000 km to be built by 2020 (Ministry of Railways of the Peoples' Republic of China (MORPRC) 2004; Li and Fung Research Centre (LFRC) 2007; Chen and Zhang 2010; Repolho et al. 2013). In the United States, 13 HSR corridors are being developed across 31 states (US DOT 2009; Landers 2010; Repolho et al. 2013).

Various critical characteristics must be addressed while planning an HSR system. These include technical design details like the type of HSR technology and rolling stock; choice of gauge; operational characteristics, i.e., whether the system will operate on an exclusive right-of-way, or on a grade separated right-of-way or on a shared right-of-way with existing conventional rail and/or freight trains, etc. HSR systems almost always operate on exclusive right-of-way or grade separated right-of-way (European Union 1996). However, in certain cases, when the infrastructure is designed to facilitate movement of HSR on conventional intercity lines, or vice versa, this flexibility of operation is known as interoperability (European Union Agency for Railways (ERA) 2016). This is typically observed when the HSR corridor being designed coincides with an existing conventional and/or freight corridor. Various prerequisites govern interoperability, which include common technical specifications for HSR and conventional rail like track gauge, signaling, existing spare line capacity for HSR, and appropriate facilities (such as stations) capable of serving the existing HSR demand (ERA 2016). Examples of integrated interoperable rail systems include SNCF in France, where HSR services share certain portions of the right-of-way with conventional rail services; Alta Velocidad Española (AVE) in Spain, where HSR lines are used by conventional trains; InterCity Express (ICE) in Germany; and Eurostar Italia, where HSR trains share the intercity rail lines with conventional trains. The advantages of such an integrated system include a seamless mode of transfer and accessibility benefits for the passengers; reduction of infrastructure cost, as existing track and stations can be used; and optimized utilization of existing rail network, as well.

Hence, it is preferred that HSR station be placed at existing intercity rail station locations. However, all existing intercity stations may not satisfy the ridership potential and inter-station spacing requirements necessary for HSR operation. Providing more stations increases the access to intermediate locations, which boosts ridership. However, this increases overall travel time. On the contrary, fewer stations or stops reduces overall ridership of the HSR. A trade-off or balance between both these objectives would yield the optimal number and location of HSR stations. A multi-objective nonlinear mixed integer model is developed in this study, which considers ridership maximization and travel time minimization. Avoiding environmentally sensitive land (such as wetlands, forests, etc.), and other requirements such as threshold inter-station distance, travel time between intended station locations, and threshold population of the intended station region, are included as environmental and corridor-specific constraints, respectively. This study proposes an artificial intelligence and geographic information system (GIS)-based heuristic methodology to evaluate and obtain the candidate set of station locations that maximize ridership and minimize travel time, such that an integrated interoperable HSR and intercity corridor can be developed. The Mumbai–Ahmedabad conventional intercity corridor is used as a case study to demonstrate the efficacy of the proposed model by identifying possible HSR station locations.

2. LITERATURE REVIEW

Addressing interoperable HSR station location and route identification involves minimization and/or maximization of objectives such as ridership and travel time along with a variety of constraints such as interstation spacing, corridor length, and threshold population. These constraints reflect the system performance requirements and/or resource limitations. This type of problem can be classified as the maximum ridership coverage/shortest path or travel time problem (Current et al. 1985; Wu and Murray 2005). Literature focusing exclusively on this type of HSR problem is lacking. However, the objectives and constraints features are similar to those of bus and rail transit design problems. The existing methods used to solve bus and rail transit route problems include analytical optimization models for idealized solutions and meta-heuristic approaches for practical situations. Analytical models are applied to predetermined transit route networks to determine one or several design parameters such as route length, route spacing, stop spacing, and location. Notable models include works by Vuchic (1969); Byrne and Vuchic (1972) on rail transit, and Lesley (1976); Wirasinghe and Ghoneim (1981); Saka (2001); Newell (1979); Leblanc (1988); Boffey and Narula (1998); Current and Schilling (1989, 1994); Hachicha et al. (2000); and Wu and Murray (2005) on bus transit. These methods were successful for problems with smaller networks or fewer decision variables, but their performance efficiency decreased for networks of larger size, having many parameters (Fan and Machemehl 2006). Meta-heuristic approaches, which can simultaneously deal with design of the transit route and associated parameters such as service routes, frequency, timetable and schedules, were developed to address the inherent complexity of such problems. Earlier works used general heuristics approaches (Silman et al. 1974; Dubois et al. 1979; Ceder and Israeli 1998), artificial intelligence-based methods (Hasselstrom 1981; Van Nes et al. 1988; Baaj and Mahmassani 1991; and Shih et al. 1997, 1998), genetic algorithm (Pattnaik et al. 1998; Chien et al. 2001; and Fan and Machemehl 2004) and simulated annealing (Fan and Machemehl 2006 and Yan et al. 2013) in solving the problem. It is evident from the review that the design of an integrated interoperable HSR and intercity conventional system needs exploration.

3. PROBLEM FORMULATION

This paper proposes a model that considers a trade-off between ridership and travel time/distance in the selection of station locations from an existing conventional rail line. In this model, total ridership and system travel distance/time is utilized to reflect the service quality. There is one major difference between the classic maximum ridership coverage/shortest-path (MRSP or MCSP) model and the proposed model. The MCSP is applied in determining a new transit route where no transit system exists, whereas the proposed model can be used for an existing transit system. The following section describes the proposed model formulation.

Let $G = (S, E, D)$ be a complete weighted graph of station locations, where S is the set of station locations denoted as $(s_1, s_2, \dots, s_{N_S})$, E is the set of edges connecting any pair of station locations denoted as $\{e_{ij}|s_i, s_j \in S\}$ $\forall$ $i, j \in \{1,2, \dots, N_S\}$, D is the distance matrix representing the pairwise distance between the given station locations denoted as $(d_{ij})_{N_S \times N_S}$ $\forall$ $i, j \in \{1,2, \dots, N_S\}$, and R is the set for ridership values for the station locations denoted as $(r_i)_{N_S}$ $\forall$ $i \in \{1,2, \dots, N_S\}$. Let IDS_{min} be the minimum distance between any two station locations, TDS_{max} be the maximum distance between terminal station locations, N_S be the total number of stations selected, NS_{max} be the maximum number of stations in an HSR corridor (based on the number of HSR station regions), and NS_{min} be the minimum number of stations in an HSR corridor. The objective function that maximizes the ridership and minimizes the travel time or distance for a selected route can be formulated as given in equations 1 and 2.

$$Max\ Z_1 = \sum_{n=1}^{N_{Smax}} \alpha_n * r_n \tag{1}$$

$$Min\ Z_2 = \sum_{i=1}^{N_S-1} \sum_{j=2, j \neq i}^{N_S} \sigma_{ij} * d_{ij} \tag{2}$$

Subject to

$$N_S = \sum_{i=1}^{N_{Smax}} \alpha_n \tag{3}$$

$$N_S \leq NS_{max} \tag{4}$$

$$N_S \geq NS_{min} \tag{5}$$

$$\sum_{i=1, i \neq j}^{N_S-1} \sigma_{ij} = 1, j \in \{2, \dots, N_S\} \tag{6}$$

$$\sum_{j=2, j \neq i}^{N_S} \sigma_{ij} = 1, i \in \{1,2, \dots, N_S - 1\} \tag{7}$$

$$\sum_{i=1}^{N_S-1} \sum_{j=2, i \neq j}^{N_S} \sigma_{ij} = N_S - 1 \tag{8}$$

$$d_{n,m} \geq IDS_{min} :\ \forall \alpha_n = 1, \alpha_m = 1,\ m = n + 1 \tag{9}$$

$$Z_2 \leq TDS_{max} \tag{10}$$

$$\sigma_{ij} = [0,1] \tag{11}$$

$$\alpha_{ij} = [0,1] \tag{12}$$

where,

$$\sigma_{ij} = \begin{cases} 1\ if\ the\ route\ goes\ from\ station\ s_i to\ s_j \\ 0\ otherwise \end{cases}$$

$$\alpha_n = \begin{cases} 1\ if\ the\ route\ covers\ station\ s_n \\ 0\ otherwise \end{cases}$$

In this formulation, the constraint related to the total number of stations for the selected route, which indirectly indicates the ridership coverage for the selected route, is represented in equation 3. Similarly, the constraint indicated by equation 4 ensures the maximum number of stations required for the selected route. Considering no intermediate stations in between the terminal stations, the minimum number of stations in an HSR corridor is two. This is represented by equation 5. Equations 6 and 7 ensure that each intermediate station is connected to exactly two different stations. The maximum number of edges or paths between selected stations is constrained by using equation 8. To ensure appropriate cruising speed and adequate distance for safe brake application, there should be sufficient distance between the consecutive stations of an HSR corridor. The constraint indicated by equation 9 ensures it. The total distance between terminal station locations should not be more than the maximum possible distance beyond which HSR travel becomes a less viable option compared to air travel (in terms of distance and travel time). Hence, the obtained route distance between the terminal stations should satisfy the maximum distance criteria. The constraint indicated in equation 10 ensures it. A weighting method (Zadeh 1963; Current et al. 1985) is used to combine the two objectives (equations 1 and 2) into a single objective problem. It is represented as equation 13.

$$Z = \emptyset Z_1/(1-\emptyset)Z_2 \tag{13}$$

Where $\emptyset$ is the assigned weightage. The objective functions, Z_1 and Z_2, are the normalized form of equations 1 and 2, respectively. It helps in representing both objective values within a common range of [0, 1]. An approximation of the non-inferior solution set can be derived by systematically varying the weight, $\emptyset$, and solving the associated single objective model.

4. SOLUTION METHODOLOGY

The exact solution can be obtained by using a brute force method, which uses the pairwise distance and ridership between all stations to check for all possible permutations between the given stations. This method is convenient for a smaller number of locations, but its efficiency reduces with a larger number of locations. This study uses ant colony optimization (ACO), similar to the one presented by Dorigo et al. (1997, 1999), to develop the route connecting the station locations. The main reason for choosing ACO is its quick convergence and efficiency in solving Hamiltonian path problem (like TSP) over other artificial intelligence-based heuristics algorithms, such as the Genetic Algorithm, Particle Swarm Optimization, and Shuffled Frog Leaping Algorithms (Brucal and Dadios 2017; Saud et al. 2018). ACO uses ants' foraging behavior by means of a pheromone trail to find the optimal solution. In this method, each ant perceives pheromone concentrations in its local environment and selects the direction with the highest concentration. This yields the best alternative i.e., the shortest path satisfying the required constraints between the two terminal stations. The working principle of ACO for the study problem is described in the subsequent paragraphs.

The number of ants, $k = 1, \ldots, n_k$, are placed at the starting terminal station. N_i^k represents the set of feasible stations connected to station s_i, with respect to ant k. Let, $T^k(t)$ denote the path or route for the ant k at time step t. Each ant k will choose the next station based on the pheromone trail associated with that move. If ant k is currently located at location s_i, then it selects the next location $s_j \in N_i^k$, based on the transition probability $P_{ij}^k(t)$, as presented in equation 14.

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\vartheta_{ij}(t)]^{\beta}\,[\delta_{ij}(t)]^{\gamma}}{\sum_{u \in N_i^k(t)}[\vartheta_{iu}(t)]^{\beta}\,[\delta_{iu}(t)]^{\gamma}} & if\ j\ \in\ N_i^k(t) \\ 0 & if\ j\ \notin N_i^k(t) \end{cases} \quad (14)$$

Where, ϑ_{ij} is the pheromone intensity between locations (i,j) and δ_{ij} is the visibility or attractiveness of the of location s_j from location s_i, which is set as $(r_i + r_j)/d_{ij}$. Whereas, β and γ are the positive constants used to amplify the influence of pheromone intensity and increase the attractiveness or desirability toward the other locations, respectively. The ACO is initiated by adding a small random value of pheromone concentration on each link. The initial amount of pheromone concentration (ϑ_{ij}) is either equal to a constant value ϑ_0 or to a random value in the range of $[0,\ \vartheta_0]$. From a station, an ant *k* would choose the next location based on the pheromone concentration-based transition probability given in equation 14. Based on the transition probability, it selects the connecting edges and incrementally progresses toward the terminal station to develop the path or corridor. Let $T^k(t)$ denote the path or corridor between the terminal stations for an ant k at time step t. Once a path is developed, the ants deterministically retrace their movement to the starting terminal station and deposit pheromone in each link, (i,j), of the corresponding path, T^k. The pheromone intensity on each link is updated after each ant leaves its pheromone trail. The pheromone trail of an ant *k* on each link (i,j) of the route T^k is proportional to the ridership $R^k(t)$, and inversely proportional to the total length $L^k(t)$ of the route traced by the ant. In other words, routes with shorter paths and higher ridership will leave a larger pheromone trail. The pheromone trail is estimated using equation 15, the length is estimated using equation 16, and ridership using equation 17.

$$\Delta\vartheta_{ij}^{k}(t) = R^k(t)/L^k(t), (i,j) \in T^k(t) \quad (15)$$

Where,

$$L^k(t) = \sum_{i,j=i+1}^{N_S-1} d_{ij}\,,\ \ (i,j) \in T^k(t) \quad (16)$$

$$R^k(t) = \sum_{i}^{N_S} r_i\,,\ i \in T^k(t) \quad (17)$$

Also, pheromones evaporate with time. The pheromone evaporation on each link (i,j), is estimated at each time step using a constant evaporation rate of μ $(0 \le \mu \le 1)$, as shown in equation 18.

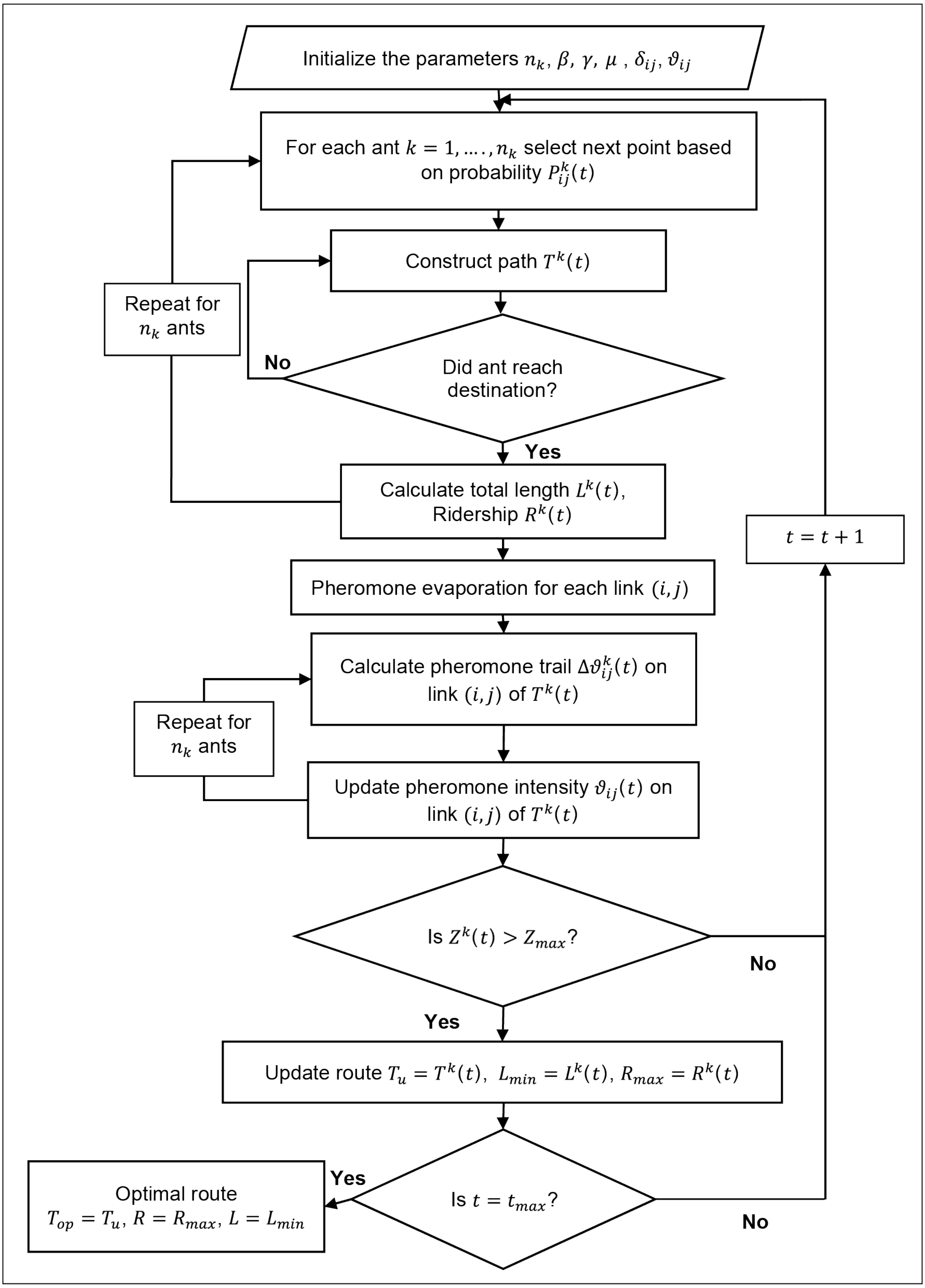
$$\vartheta_{ij}(t+1)=(1-\mu\,)\vartheta_{ij}(t) \quad (18)$$

Combining equations 15 and 18, the updated total pheromone concentration on each link (i,j) at time step *t* can be estimated using equation 19.

$$\vartheta_{ij}(t+1) = (1-\mu\,)\vartheta_{ij}(t) + \sum_{k=1}^{n_k}\Delta\vartheta_{ij}^{k}(t) \quad (19)$$

The process continues until the stop criteria is met. In the end, the route with the highest pheromone concentration is considered as the shortest possible route with maximum ridership. The working principle of the ACO is illustrated in the Figure 1.

Figure 1: Flowchart for Corridor Identification Using ACO



5. CASE STUDY

The proposed Mumbai–Ahmedabad HSR corridor connecting the cities Ahmedabad in Gujarat and Mumbai in Maharashtra is considered as the case study. It is India's first HSR project. The Mumbai–Ahmedabad conventional intercity rail corridor is analyzed using the proposed model to identify the possible HSR station locations. The conventional intercity rail corridor between Mumbai and Ahmedabad has about 28 major stations with as many as 69 long distance trains (Erail 2018).

Number of Intercity Origin Destination Pairs. The threshold value of population in cities along a corridor for HSR implementation is 500,000 (Takeshita 2012). The latest census data available for Maharashtra and Gujarat is for the year 2010–2011 (Chandramouli and General 2011). It was extracted from the Census of India website (ORGCC 2016) in Excel spreadsheet table format. The population data was available for each state, district, sub-district or taluka, city, and village. A search program was developed using Python programming language to identify sub-districts and cities with estimated population levels over the threshold value for HSR implementation. In the process, 11 potential regions satisfying the population threshold were identified in the states of Maharashtra and Gujarat. It included Ahmedabad, Anand, Bharuch, Vadodara, Surat, Valsad, Vapi, Thane, Boisar, Vasai-Virar, and Mumbai.

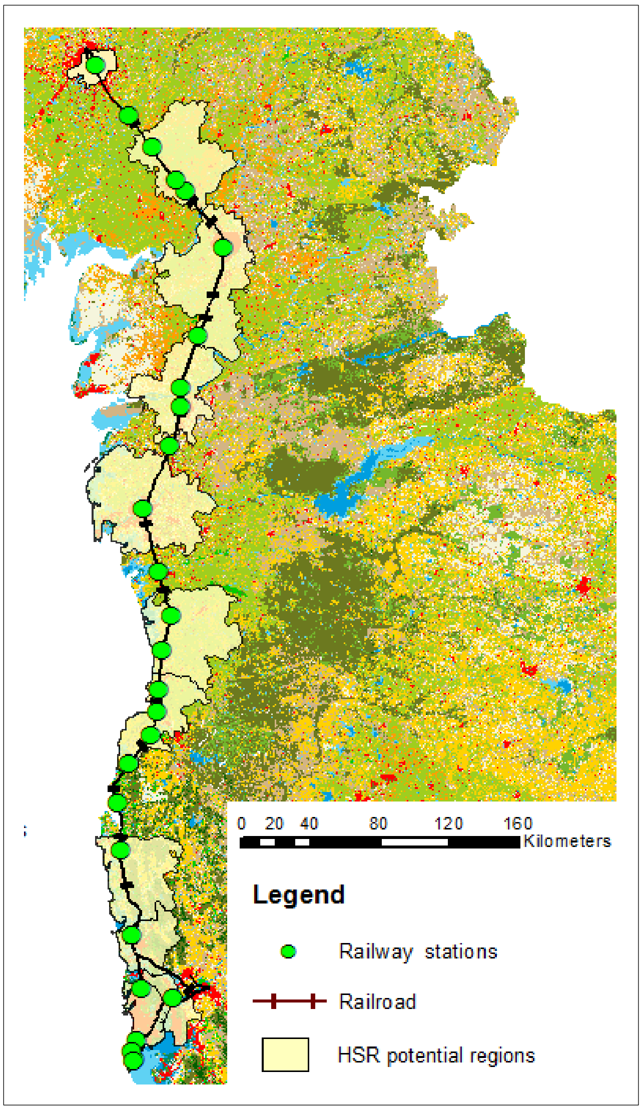
GIS Shapefiles. GIS data was downloaded from the OpenStreetMap website (2017), in the form of vector shapefiles. It included point shapefiles for locations; transportation points (bus stops, railway stations); polyline shapefiles for railway, highway and road networks; and polygon shapefiles for buildings, political/administrative boundaries, and waterbodies. The shapefile showing conventional rail station locations was used as input. Table 1 shows the input parameters used in this study, and Figure 2 represents the study area along with the existing intercity railroad, railway stations, and HSR potential regions.

Table 1: Input Parameters

Input Parameters	Values	Source
Factors Controlling Trail $\boldsymbol{\beta}$	1.0	Brezina and Cickova 2011
Factors Controlling Visibility $\boldsymbol{\gamma}$	2.0	
Pheromone Evaporation Rate $\boldsymbol{\tau}$	0.5	
Number of Ants $\boldsymbol{n_k}$	500	Assumed
Maximum Number of Generations	400	Assumed
Distance between Consecutive Stations $\boldsymbol{IDS_{min}}$	24 km	Stanford Research Institute 1968
Maximum Distance between Terminal Stations $\boldsymbol{TDS_{max}}$	800 km	Takeshita 2012
Minimum Number of Stations in the Corridor $\boldsymbol{NS_{min}}$	2	Assumed
Maximum Number of Stations in the Corridor $\boldsymbol{NS_{max}}$	11	RITES 2013; JICA 2015

Ridership data. Ridership data was obtained from the report on the Joint Feasibility Study for Mumbai–Ahmedabad High Speed Railway Corridor (2015) prepared by JICA, in the form of boarding and alighting passengers per day in both directions. The ridership data adopted for this study was for the horizon year 2023.

Figure 2: Study Area



Source: Bhuvan 2016.

6. RESULTS

The ArcGIS version 10.2, a commercial GIS package by ESRI Inc. (U.S.A.) was used for travel time, distance estimation, data management, and result visualization. Furthermore, a Python-based script, supported by ArcGIS, was specifically developed to implement the proposed model. A 3.6 GHz Intel® Core™ i7 processor-equipped personal computer, with 8 GB memory, was used to run the GIS-integrated Python script. It was run by varying the values of weightage factor $\emptyset$ for sufficient number of iterations until the results converged. The obtained results are displayed in Table 2.

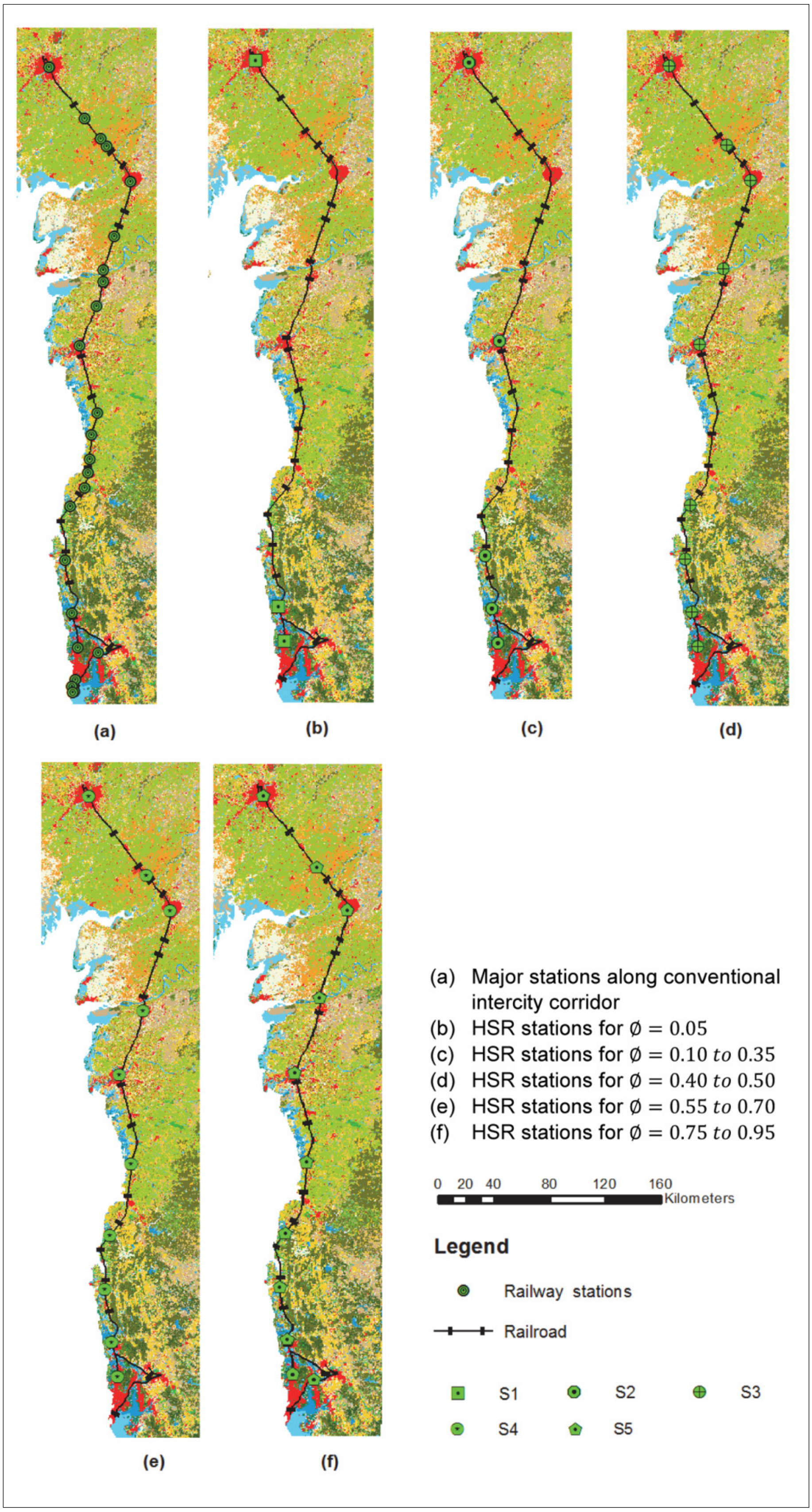
The trade-off between ridership coverage and travel distance is presented in Table 2. A steep change in travel distance, ridership, and access coverage can be observed when $\emptyset$ changes from 0.35 to 0.4. Similarly, phenomenon was observed when $\emptyset$ changes from 0.7 to 0.75. Hence, for this study, a weightage factor variation between 0.4 and 0.7 would provide a reasonable trade-off between ridership and access coverage and travel distance, as the variation in travel distance with ridership and access coverage is significantly less within this range. Figure 3 shows the station locations for the existing intercity corridor and the station locations that satisfy the criteria for integrated interoperable HSR system.

Table 2: Ridership Coverage and Travel Distance Trade-off

Weightage ∅	Ridership Covered Z_1 (pass./day)	Travel Distance Z_2 (km)	Ridership per Distance Unit	Number of Stations	Number of Generations
0.05	53,000	421.48	125.7474	3	2
0.10	59,000	422.96	139.4931	5	6
0.15	59,000	422.96	139.4931	5	6
0.20	59,000	422.96	139.4931	5	6
0.25	59,000	422.96	139.4931	5	5
0.30	59,000	422.96	139.4931	5	8
0.35	59,000	422.96	139.4931	5	7
0.40	72,000	445.70	161.5436	9	2
0.45	72,000	445.70	161.5436	9	9
0.50	72,000	445.70	161.5436	9	11
0.55	73,000	448.29	162.841	10	7
0.60	73,000	448.29	162.841	10	17
0.65	73,000	448.42	162.7938	10	7
0.70	73,000	448.42	162.7938	10	9
0.75	76,000	472.69	160.7819	11	9
0.80	76,000	472.69	160.7819	11	32
0.85	76,000	472.69	160.7819	11	19
0.90	76,000	472.69	160.7819	11	13
0.95	76,000	472.69	160.7819	11	13

The major station locations in the study area are presented in Figure 3(a). The station locations for weightage factor of 0.05 (indicated by S1) are shown in Figure 3(b), which has the minimum end-to-end travel distance and the least number of intermediate stations. However, the ridership coverage is also the lowest due to limited access (see Table 2). Similarly, Figure 3(c) represents the station locations (indicated by S2) for the weightage factor varying from 0.10 to 0.35. This route has a total of three intermediate stations and satisfies a higher ridership coverage due to higher access points. The ridership coverage increases at weightage factor of 0.40 and remains steady until it reaches a factor of 0.50. Figure 3(d) represents the station locations (indicated by S3) for the weightage factor between 0.40 and 0.50. It increases again at weightage factor 0.55 and remains steady until it reaches 0.70. The station locations (indicated by S4) for this range of weightage factors are presented in Figure 3(e). The ridership per unit distance also shows an increasing trend up to these weightage factors. Thereafter, for weightage factors between 0.75 and 0.95, the ridership coverage increased but the ridership per unit distance decreased. The station locations (indicated by S5) for this range of weightage factors are presented in Figure 3(f). As indicated earlier, the ridership per unit distance is maximal for weightage factor between 0.4 and 0.7. So, the stations locations presented in Figures 3(d) and 3(e) may be considered suitable for the integrated interoperable HSR system.

Figure 3: Stations along Mumbai–Ahmedabad Corridor



7. CONCLUSION

Integrated interoperable rail systems facilitate the movement of HSR trains on conventional intercity lines, and vice versa. Hence, it is preferred that HSR stations exist at intercity rail station locations. However, all existing intercity stations may not satisfy the ridership potential, corridor length, and inter-station spacing requirements necessary for the HSR operation. Providing more stations increases the access to intermediate locations, which boosts ridership. However, it also increases overall travel time and distance. On the contrary, fewer numbers of stations or stops reduces overall ridership of the HSR. Hence, a trade-off or balance must be obtained, where a required amount of ridership potential is met without increasing the travel time and distance significantly.

This paper proposes a GIS-based interoperable HSR station location identification approach along existing intercity rail lines to identify suitable integrated interoperable HSR and intercity station locations. A ridership maximization, and travel time or distance minimization formulation is developed. Suitable weightage factors are used to combine these conflicting objectives into a single objective function. The threshold inter-station travel time or distance between the selected station locations, total end-to-end corridor travel time or distance and the threshold population of the selected station regions are included as corridor-specific constraints. A heuristic approach is used to evaluate and obtain the candidate set of station locations. This paper utilizes ant colony optimization as the heuristic method to optimize the formulated problem. The Mumbai–Ahmedabad conventional intercity corridor is used as a case study to demonstrate the efficacy of the proposed model by identifying possible HSR station locations along the intercity rail corridor.

Variation in station location results can be observed with the change in weightage factor. For the case study considered, higher weightage toward ridership coverage (more than 0.7) increases the travel distance significantly, whereas lower weightage (less than 0.35) yields poor ridership results. It can be inferred that HSR planners can come up with station locations along conventional intercity rail lines that satisfy the travel time or distance and ridership requirements necessary for developing or designing an interoperable HSR system. However, the weightage factor should be selected judiciously. The intermediate station locations that do not satisfy the selected criteria can be eliminated beforehand. It would reduce the computation time.

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