# AN EVOLUTIONARY MODEL FOR OPTIMIZING RAIL TRANSIT STATION LOCATIONS 

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doi:10.23918/iec2018.06


#### Abstract

Optimizing rail transit station locations is a very complex engineering problem. The requirements and constraints that should be considered in locating rail transit stations are complex and interrelated. Although several optimization models have been developed to solve the rail transit station location problem, most of them focus on a single objective and only yield a suboptimal solution to the problem. Multipleobjective models for optimizing rail transit station locations are rare in the literature and their capabilities are very limited. This paper, addresses the limitations in the existing models by developing an evolutionary model, taking into account various local conditions and the multiple planning requirements that arise from passenger, operator and the community to optimize station locations. The model uses an evolutionary solution algorithm (a search algorithm that imitates the natural evolution process) based on genetic algorithm (GA) integrated with geographic information system (GIS) tools to perform the optimal search. The model was applied to an artificial case study and the results demonstrate that the model can optimally locate stations that satisfied the identified planning requirements and constraints.


Keywords: Rail Transit Station, Optimization, Genetic algorithm, GIS.

## 1. INTRODUCTION

Continuous growth of urban areas and associated needs for mobility have given rise to the need for building new rail transit systems or expanding existing ones. A rail transit system can play a crucial role in reliving transport problems, such as congestion, increased travel time and air pollution. At the same time, it can also provide safe, reliable and convenient service for population within major corridors and to important activity areas. However, the establishment of a rail transit system requires massive investments and exerts permanent impacts on the travel pattern, land use development and even environmental characteristics across potential service areas. Therefore, its actual implementation requires rigorous planning and evaluation processes. The planning of a rail transit system involves determination of station locations and network of lines linking the stations. It is, however, a truism that rail transit stations represent a point at which people can have access to a rail transit system and that it is an important factor for a rail transit system to be selected as an alternative transport mode. Therefore, rail transit stations represent a crucial part of the planning process. The determination of station locations requires consideration of various local factors including travel demand patterns, land use patterns, existing transport network, and topography while satisfying a number of complex and interrelated requirements of the various rail transit system stakeholders (passenger, operator and the community). This necessitates the application of optimization models to achieve an optimal (reliable and cost effective) solution. Subsequently, this paper formulates the rail transit planning process as an optimization problem to seek the optimal locations of stations. It is, however, difficult to model the rail transit station requirements with simple mathematical functions due to their complexities which involve non differentiable, nonlinear, discontinuous structure. Therefore, an evolutionary optimization algorithm based on a GA is designed to efficiently solve the problem. A GA is an evolutionary optimization technique widely utilized for solving various complex problems. Following the concept of biological evolution, a GA evolves a population of different alternative solutions towards the optimal solution. The evolution begins with a population of random alternative solutions and progresses over a number of generation/iterations. In each generation/iteration, the fitness of the population is evaluated with respect to the desired objectives of the problem. Thereafter, a number of individuals are selected stochastically from the
current population based on their fitness values and modified with genetic operators (crossover and mutation) to produce a new population for the next generation/iteration. This process is continued until a specified number of generations, which is fixed a priori, either have elapsed or other predetermined convergence criteria are met $[1,2]$.

## 1. LITERATURE REVIEW

Many researchers and planners have made many attempts to develop various optimization models for solving rail transit station location problem. Vuchic and Newell [3] developed an analytical model to determine spacing between stations along a predetermined rail line. With respect to the objective of minimum passenger travel time, the model calculated interstation spacing by solving a set of partial differential equations specifying the optimality condition. Vuchic [4], Kikuchi and Vuchic [5], and Wirasinghe [6], considered various improvements to the Vuchic and Newell's approach for determining the optimal station spacing. However, these models have only limited practical applications due to oversimplification of the problem by assuming uniform distribution of population along rail transit lines and that the population of an area served by the rail line commutes to one central points. Recent studies therefore, attempted to further improve these models through removing unrealistic assumptions and incorporating various planning and real world constraint requirements. Laporte et al., [7] developed a model for locating a prefixed number of stations on a predetermined rail transit alignment with the objective to maximize population coverage while satisfying interstation spacing constraint. The study estimated the demand for each potential station by triangulation of census tracts, assuming that the percentage of the captured travellers decreases with their access distance from the station. Schöbel et al. [8] presented a model to locate additional stations along existing rail line networks, considering the trade-off between positive and negative effects of additional stations. The objective of the model was to minimize the number (cost) of additional stations while ensuring coverage of all demand centers. The demand center, which may represent a settlement area, shopping center, school, etc., was assumed to be covered if the next station was within a specified radius from it. In an extended effort, Hamacher et al. [8] built up on Schöbel et al. [9]
study by seeking to satisfy two different objective functions of demand covering and accessibility to stations. Following the same approach, Carrizosa et al. [10] proposed a model seeking a set of additional stations covering all demand centers but, instead of minimizing the number of additional stations, the additional passenger travel time due to the additional stations were minimized. In another study, Jha and Oluokun [11] addressed the determination of the optimal station locations along a predetermined rail transit alignment using artificial intelligence based optimization techniques and GIS. Similarly, using GIS tools Samanta and Jha [12] used GA to seek the best set of station locations along a rail transit line to minimize total system cost while ensuring that the interstation distances remain constraints. The model defined the total system as a function of passenger total travel time, system operation and construction costs. Despite the capabilities of the aforementioned optimization models in addressing many aspects of rail transit station locations, most of them have a number of limitations that necessitate further improvements in order to achieve optimal (reliable and cost effective) solution to the problem. These limitations include: (a) primarily, many of these models neglect initial feasibility study to identify potential station locations, assuming that rail transit stations can be located anywhere in the study area or along the rail transit line without considering the various environmental, topological and budget constraints; (b) most of these models disregard the effects of various local factors of the study area, such as land use pattern, land values, existing roadway network and topography on the overall system performance and cost and; (c) many of these models address partial aspects of the problem by focusing mainly on the coverage of traffic demand or population with other critical passenger, operator and community related aspects being ignored. This paper addresses these limitations by developing a new evolutionary based model integrated with GIS tools to determine the optimal set of station locations for a rail transit line. The proposed model takes into account initial feasibility of station sites, various local factors and multiple planning requirements that arise from passenger, operator and the community.

## 3. THE MODEL FRAMEWORK

The model framework comprises two stages, as shown in Figure 1. In the first stage, the model measures the feasibility of station sites to identify a pool of feasible station locations using a GIS-based algorithm. In the second stage, the model selects the best set of stations from the feasible station pool identified in the first stage using an optimization procedure based on a GA while interacting with GIS supporting system. Once the optimal station locations are determined, they are connected to obtain the rail line alignment. However, since the focus of this paper is to find optimal station locations along a rail transit line, it is assumed that the final alignment of the rail line is obtained through the linear connections of the stations. The mathematical formulations of these two stages are discussed and detailed in the next section.


FIGURE 1. The Model Framework

## 4. MATHEMATICAL FORMULATION

As mentioned in section 3, prior to the optimization process the model evaluates the feasibility of station locations to identify a candidate pool of stations using a GISbased algorithm. Performing such a feasibility analysis can effectively speed up the planning process and improve decision-making in selecting reliable and cost effective solutions. This is by: (1) excluding environmental protected areas that may result in significant unnecessary increases in the station construction cost from the optimization search space. In addition, the exclusion of these areas results in significant decreases of computation time in exploring unnecessary areas of the search space (2) identifying areas that have high intensity of residential and commercial land use areas. The coordination of rail transit stations with these land use areas can significantly increase the number of potential passengers utilizing the system, which
in turn results in reduced overall vehicle travel, and thereby reduced traffic congestion and improved mobility. The proposed GIS-algorithm applies the following three main steps to screen the potential served area and perform evaluation analysis for generating a pool of feasible station locations.

Step 1: dividing the study area into grids $\left(\mathrm{G}_{i}\right)$ and creating a GIS layer for stations $\left(\Omega_{s t}\right)$. It is assumed that each of the generated grids represents a potential location for a rail station. The size of each grid, therefore, should represent the typical size of a rail station.

Step 2: finding all station grids that intersect with environmentally protected areas and excluding them from the search space of feasible station locations. This is done by laying the generated station grid layer $\left(\Omega_{\mathrm{st}}\right)$ over the environmentally sensitive areas layers ( $\Omega_{\mathrm{env}}$ ) to generate the feasible grid layer for station $\left(\Omega_{\mathrm{fs}}\right)$. The environmentally protected areas include historic buildings, green parks, woodlands, rivers and sites of scientific interest.

$$
\begin{equation*}
\Omega_{f s}=\Omega_{s t} \cap \overline{\Omega_{e n v}} \tag{1}
\end{equation*}
$$

Step 3: identifying all the grids within the feasible station layer $\left(\Omega_{\mathrm{fs}}\right)$ with the average commercial land use areas within the defined walking distance of stations greater than the pre-specified threshold value of commercial land use areas and assigning them with an integer value. In this paper, the commercial land uses areas include recreational centers, shopping malls, office complexes, industrial complexes and university campuses.

$$
\begin{equation*}
\forall G_{i} \in \Omega_{\mathrm{fs}} \rightarrow=1 \text { if }\left(\sum \overline{C A} \mid \mathrm{D}_{\mathrm{w}}\right) \geq \mathrm{V}_{\mathrm{CA}} \tag{2}
\end{equation*}
$$

Where: $\overline{C A}$ is the average commercial land use areas within walking distance of station; $\mathrm{D}_{\mathrm{w}}$ is the defined walking distance to stations and; $\mathrm{V}_{\mathrm{CA}}$ is the pre-specified threshold value of average commercial land use areas within $D_{w}$.

Step 4: identifying all the grids within the feasible station layer $\left(\Omega_{\mathrm{fs}}\right)$ with the average population density within the defined walking distance of stations greater than the prespecified threshold value of population density and assigning them with an integer value.

$$
\begin{equation*}
\forall G_{i} \in \Omega_{\mathrm{fs}} \rightarrow=1 \text { if }\left(\sum \overline{P D} \mid \mathrm{D}_{\mathrm{w}}\right) \geq \mathrm{V}_{\mathrm{PD}} \tag{3}
\end{equation*}
$$

Where: $\overline{P D}$ is the average population density within $\mathrm{D}_{\mathrm{w}}$ and; $\mathrm{V}_{\mathrm{PD}}$ is the pre-specified threshold value of average population density within $\mathrm{D}_{\mathrm{w}}$.

Once the pool of feasible station locations is generated, the model selects the best set of stations from the generated pool within the context of an optimization procedure using an evolutionary search algorithm based on a GA supported by a background GIS database. The optimization framework is designed to accommodate various local factors, incorporate multiple objectives and constraints that arise from passenger, operator and community requirements and compute the optimal solution. The objective of the optimization process is to minimize passenger, operator and community costs. The following are key steps of the developed GA based optimization algorithm:

Step 1: generating the alternative solutions (i.e., population) by randomly selecting a set of stations $\left(\mathrm{S}_{\mathrm{i}}\right)$ from the station pool generated in the first stage and connecting them linearly while ensuring that: (a) the number of the selected stations falls within predefined minimum ( $\mathrm{Ns}_{\text {min }}$ ) and maximum ( $\mathrm{Ns}_{\text {max }}$ ) limits set by rail transit system planners and; (b) the distance between selected stations fall within predefined minimum ( $\Delta \mathrm{s}_{\text {min }}$ ) and maximum ( $\Delta \mathrm{s}_{\text {max }}$ ) station spacing. It is assumed that, depending on the major traffic flow patterns of the area to be served, rail transit system planners are able to locate the terminal stations prior to the optimization process. That is, the model seeks the best locations of intermediate stations.

Step 2: evaluating the fitness value of each alternative solution which is a function of three main components; passenger, operator and community costs.

$$
\begin{equation*}
T_{C}=P_{C}+O_{C}+C_{C} \tag{4}
\end{equation*}
$$

Where: $T_{C}$ is the total system cost $(\$), P_{C}, O_{C}, C_{C}$ are the passenger, operator and community costs (\$) respectively.

$$
\begin{equation*}
\mathrm{P}_{\mathrm{C}}=\mathrm{T}_{\mathrm{a}} \times \mathrm{A}_{0}+\mathrm{T}_{\mathrm{w}} \times \mathrm{W}_{0}+\mathrm{T}_{\mathrm{t}} \times \mathrm{T}_{0} \tag{5}
\end{equation*}
$$

Where: $\mathrm{T}_{\mathrm{a}}$ is the passenger's access time to/from station (min); $\mathrm{A}_{0}$ is the costs of access time $(\$ / \mathrm{min}) ; \mathrm{T}_{\mathrm{w}}$ is waiting time at station ( min ); $\mathrm{W}_{0}$ is the cost of waiting time $(\$ / \mathrm{min}) ; \mathrm{T}_{\mathrm{t}}$ is on train travel time ( min ) and; $\mathrm{T}_{0}$ is the unit cost of on train travel time ( $\$ / \mathrm{min}$ ). The passenger access time to/from rail stations is a function of the passenger walking distance and speed to/from stations. It is computed through artificial links that created between traffic analysis zones (TAZs) and feasible station locations. These links measure the distance between the centroids of the each TAZ and feasible station location $\left(D_{a}\right)$, thus the access time is calculated by dividing this distance $\left(D_{a}\right)$ to passenger walking speed $\left(\mathrm{V}_{\mathrm{a}}\right)$. The waiting time is assumed to be equal to half of the train headway $\left(H_{w}\right)$ which is a function of train frequency. The on-train travel time is calculated by dividing the distance between boarding and alighting station $\left(D_{s}\right)$ by the train speed $\left(V_{t}\right)$.

$$
\begin{equation*}
O_{c}=L_{t} \times M_{0} \tag{6}
\end{equation*}
$$

Where: $L_{t}$ is the total train km travelled distance and ; $M_{0}$ is the unit operation and maintenance cost for train ( $\$ / \mathrm{km}$ ).

$$
\begin{equation*}
C_{C}=L_{S}+B_{S} \tag{7}
\end{equation*}
$$

Where: $L_{S}$ is the land acquisition cost for stations (\$); $B_{S}$ is the cost of building stations (\$). The land acquisition costs are fed into the evaluation process via interaction with GIS while the cost of building stations is assumed to be fixed.

Step 3: evolving the initial solutions generated in step 1 over a series of generations/iterations based on their fitness values calculated in step 2 to converge towards the optimal solution. This is by applying three genetic operators, selection, crossover and mutation, adopting the approach developed by [13]

Step 4: terminating the evolution process when searching through the predefined number of generations is reached or improvement in the objective function value is negligible (less than 1\%).

## 5. CASE STUDY

The effectiveness of the proposed model was examined by applying it to an artificial case study. The size of the case study was $36 \mathrm{~km}^{2}$ ( $8.0 \mathrm{~km} \times 4.5 \mathrm{~km}$ ). Each of the land use pattern, population density and land value datasets were created artificially for the study area and digitized for the analysis purpose. The land use pattern dataset contained commercial land use areas and environmentally protected areas. As discussed in section 4, the commercial land use areas include recreational centers, shopping malls, office complexes, industrial complexes and university campuses while the environmentally protected areas include historic buildings, green parks, woodlands, rivers and sites of scientific interest. After the preparation of the required datasets and defining the model input parameters, the model was implemented. Figure 2 presents the candidate pool of feasible station locations generated in stage 1 of the model evaluation process. It is very interesting to note that the candidate feasible stations mainly cover the most densely populated and commercial areas of the study area. This is in addition to excluding the environmentally protected areas from the search space. These results indicate that screening the study area for feasible station locations prior to the optimization process plays an important role in directing the search towards the promising region of the search space.


FIGURE 2. Generated Feasible Station Locations

Figure 3 shows the best locations of stations, obtained in stage 2 of the model evaluation process, which were selected from the generated feasible station pool. The optimal solution consists of 7 stations, covering more than 138,700 people within 800 meters walking distance of stations, which comprises almost 27 percent of the case study's total population. Furthermore, the obtained solution covers more than 45 percent of the case study's commercial areas, which include recreational areas, shopping malls, office complexes and industrial complexes within 800 meters walking distance of the stations. These results, therefore, indicate that the model can effectively find a robust and reliable solution.


FIGURE 3. Optimized Station Locations

## 6. CONCLUSION

This paper presented an evolutionary optimization model for locating rail transit stations. The model first evaluated the feasibility of the potential served area to generate a pool of feasible stations considering various local and environmental factors. The best set of these feasible stations were then selected within the context of an optimization process using GA while interacting with GIS supporting system. The optimization framework accommodated complex correlation and interaction of the multiple requirements and constraints arising from different rail transit system stakeholders; passenger, operator and the community, and made trade-off between them in order to achieve a reliable and cost effective solution. To demonstrate its
effectiveness in finding good solutions, the model was applied to an artificial case study. The results revealed that the model can effectively resolve the essential tradeoff between minimum passenger travel time and operation and maintenance cost on the one hand, and the minimum construction cost of the stations on the other hand, while also satisfying various constraints. Furthermore, the results revealed that performing a feasibility analysis for potential station locations prior to the optimization process can effectively improve the performance of the model to realize an optimal (reliable and cost effective) solution, by directing the search to explore the most promising regions in the search space.

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