

Optimizing skip stop scheduling in the Washington Metro Silver Line using genetic algorithms

Anoop Hariharan

Loudoun Academy of Science

Abstract

Skip stopping scheduling is a transportation optimization technique developed to reduce overall travel costs. It is most commonly applied to metro systems that do not have a second rail for express trains to pass. Thus, skip stopping does not require much new investment to reduce overall travel costs. This project initially applied a continuous approximation model to the skip stopping model to identify the cost associated with skip stopping for the Washington Metro Silver Line. However, due to issues with dimensional analysis and derivations of the formulas used in the continuous model paper (Freyss, Giesen, & Muñoz, 2013), the project shifted to a genetic algorithm approach found in a paper applied to a Korean metro line. This approach not only provides a total cost associated with skip stopping, but also gives each station's type (A, B, AB) (Lee, Shariat, & Choi, 2014). Although results could not be collected due to errors with the program, the project did provide a valuable insight into the many factors that need to be considered when developing a realistic skip stop model.

Introduction

Skip stopping has been a major theme in transportation optimization research because it is a valuable tool to increase travel speed without developing much new infrastructure. As such, it has been discussed for many years now in transportation optimization papers. In fact, some of the papers addressing the AB skip stopping method are more than 40 years old (Vuchic, 1976). Though the AB skip stopping method has been found in much of the research on this topic, the exact method by which it is carried out has differed. For example, a continuous model was used to approximate the effect of an AB skip stopping pattern on travel costs in Chile. However, the

limitation of this model was that it could not actually output the specific stations to skip and did not take into account origin-destination data. Thus, it could only approximate the effectiveness of a skip stopping pattern but not show the exact method by which it could be accomplished most efficiently. This paper still found that shorter lines with few stations and low frequency lines would not benefit significantly from skip stopping (Freyss, Giesen, & Muñoz, 2013). Along with continuous models, there have also been combinatorics approaches to the problem of optimizing the skip stop pattern. These approaches usually take into account the different combinations of station types that can be created and use them as input variables for a fitness function of a genetic algorithm. Typically, these fitness functions are related to the total travel time of the passenger. Since the combinations of station types can be exceedingly high to compute using a brute force search, the genetic algorithm is used to arrive at an approximate answer. A paper applying the genetic algorithm approach to the Shenzhen metro in China found that the optimization produced a lower travel time than the traditional “all-stop” pattern. Of note, however, is that this paper utilized a Flexible Skip Stopping Scheme (FSSS) rather than the AB scheme (Zhang, Sun, & Liu, 2017). Genetic algorithms have also been used for the traditional AB skip stopping approach. In a paper utilizing data from a line on the Korean metro (Lee, Shariat, & Choi, 2014), the genetic algorithm took as inputs vectors with three possible values in each row, each corresponding to one of the three station types in an AB pattern. This model also output a set of stations to be skipped and stopped at. In addition, it took into account origin and destination demand (Lee, Shariat, & Choi, 2014). The research question for this project was whether a skip stopping pattern would be beneficial on the Washington Metro Silver Line. Based on previous research

that identified benefits from using a skip stop pattern, it seemed likely that a skip stop pattern would provide a decrease in travel cost (Lee, Shariat, & Choi, 2014)..

Materials and Methods

To develop this project, the Python Spyder application was used. This application provided an environment in which the python code could be written in a readable format and the output of the program could be seen. Within the Python spyder application, various addons were used from third party sources such as matplotlib and xlwings. Matplotlib provided the functionality to output graphs, though this was not possible in this project because the output could not be generated due to errors in the program (addressed in the discussions section). The xlwings addon provided the ability to connect Python to an Excel file, which was the format in which the metro system released their data. The genetic algorithm code was modified from a tutorial source which applied it to a different purpose (Nicolle, 2017). The origin destination data for this project was taken from the planitmetro.com website and modified in Excel to create a file from which the program could easily iterate over.

The genetic algorithm written in Python consisted of a few main functions: fitness, mutation, crossover, and random generation. The fitness function was written almost entirely from scratch and is essentially the same as the travel cost associated with a particular station vector. The other functions were modified from the tutorial source (Nicolle, 2017). The mutation function modifies a random row in the station vector (corresponding to a station) and then

randomly changes its type. This prevents the algorithm from settling at a local minimum on the fitness function. The crossover function chooses two chosen station vectors from the population, some of which are of high fitness and some of which are randomly chosen (to again prevent settling at local minimums). The function then merges these two station vectors to produce a more “evolved” station vector, which is ideally closer to the solution than the parent station vectors. The random generation function actually happens in the beginning, and it creates a population of random station vectors, with the first value of the vector always equal to 2 (the value for an AB station).

The data file that was downloaded from the planitmetro.com website gave the origin destination data for the month of October in 2014. From this data file, a filter was used to identify the average AM peak ridership on weekdays between the origin-destination pairs on the first five stations of the Silver Line. Only the first five stations of the Silver Line were used for this project because they did not share tracks with other lines. This is further elaborated upon in the discussion section. Along with the average AM peak ridership on weekdays for a given OD pair, the standard travel time was also included in another row. This was found by searching for the time taken to travel between the origin and destination on Google Maps. The transit function was used on Google Maps, which made it easy to find the standard travel time between a station pair.

The main component of the genetic algorithm is the fitness function, which took as an input a station vector and output a total travel time cost, also termed fitness. The fitness function took into account factors like transfer time and transfer time.

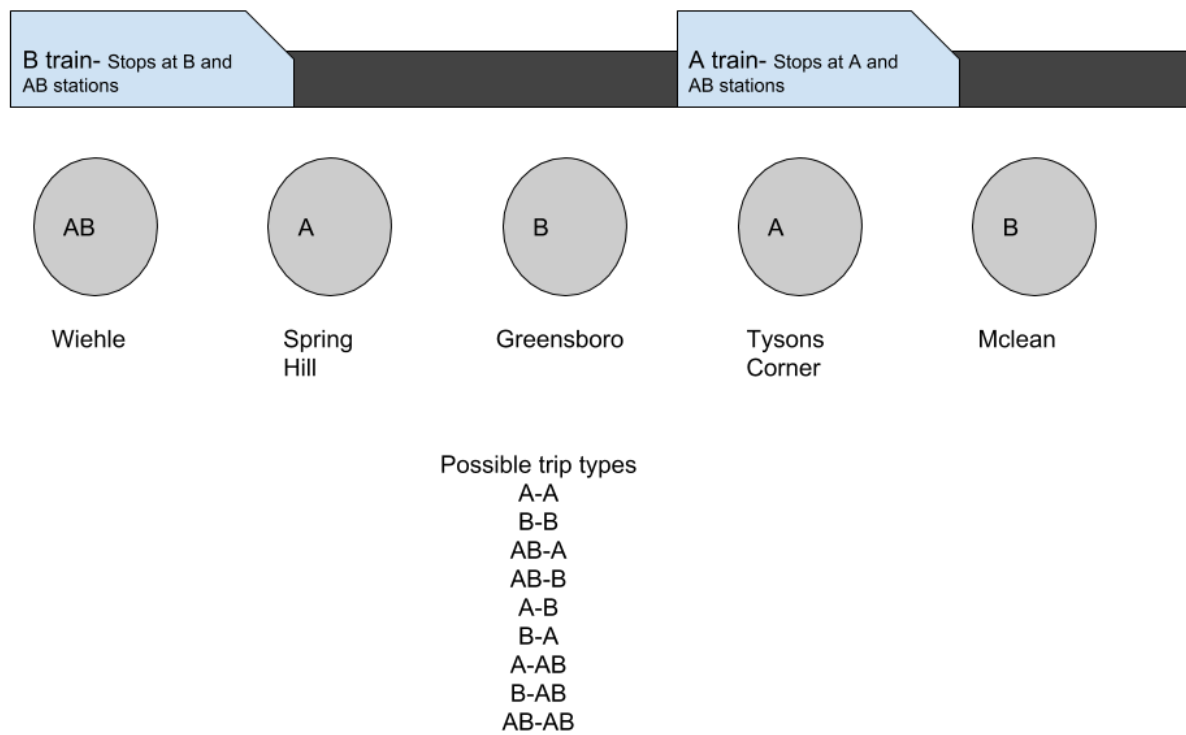


Figure 1: Outline of the AB skip stopping pattern for the five station considered on the silver line. This graphic was also used on the presentation board.

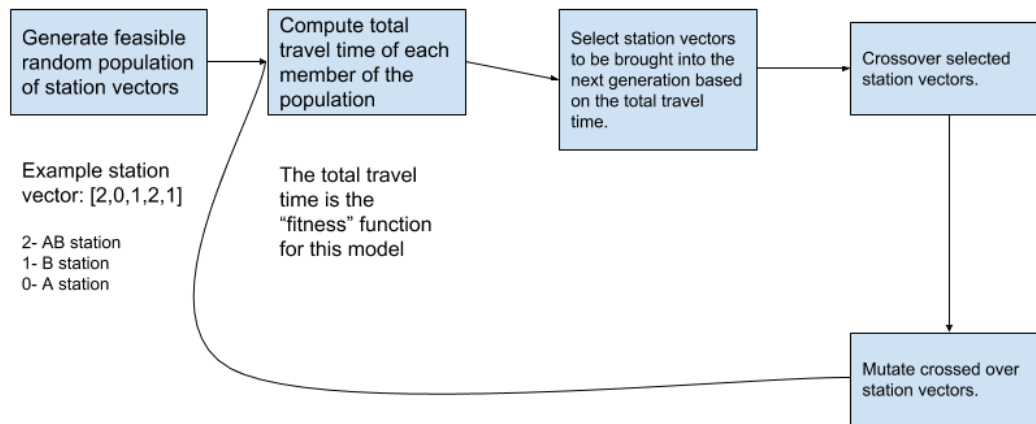
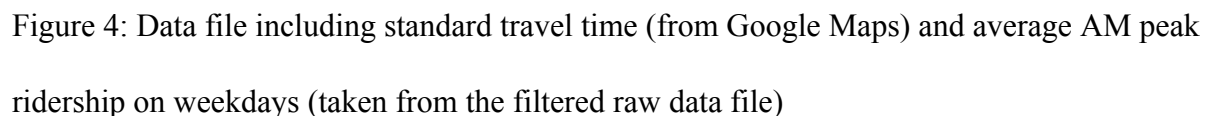
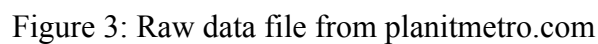


Figure 2: Outline of the genetic algorithm process as it relates to skip stopping. This graphic was also used on the presentation board.

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The screenshot shows the Spyder Python IDE interface. The top toolbar includes icons for Run, Debug, Consoles, Projects, Tools, View, and Help. The main editor window displays a Python script named 'genAlg.py' with the following code:

```

39 for i in range(1, populationSize+1):
40     populationStationVector.append(generateRandomStations())
41

```

The right-hand pane shows the 'Python console' with the output:

```

nextBreeders =
populationSelection(populationSorted, best_sample

```


Figure 5: Snippet of fitness function code- `travelTime()`

Due to the errors in the program, an output could not be generated.

Discussion

It can be concluded that there is certainly the data available to conduct a genetic algorithm based skip stop optimization of the Washington Metro Silver Line. However, the multitude of different factors that have to be considered make its development time much longer than a continuous model like that applied to the Chile metro (Freyss, Giesen, & Muñoz, 2013). However, the benefit of being able to view the exact stops that can be skipped (which a continuous model cannot do) seems to be more useful.

Since results could not be collected, the effectiveness of the model could not be tested. However, the conceptual limitations of the model can still be addressed. The fitness function that was ultimately developed for the genetic algorithm had multiple limitations. First, it assumed a waiting time of zero when computing the total travel cost. Though this simplified the function, it is unrealistic because most people will not arrive exactly at the time that a train arrives at a station. This error would be seen especially in skipped stations, because the maximum headway of a passenger arriving at a skipped station would be higher than at an all stop station. The effect of this is that the total travel cost would appear lower than the actual value if waiting time were

taken into account. Indeed, the model used on the Korean metro addressed this issue (Lee, Shariat, & Choi, 2014). In addition, no collision constraints were used unlike the model applied to the Korean metro by past research (Lee, Shariat, & Choi, 2014). It was assumed that for this model, collisions would not be an issue since the maximum time that could be saved was four minutes (as only five stops were considered on the silver line). Since the highest frequency on the silver line is still 8 minutes, it was assumed that there would always be room between two trains even if 4 minutes were saved on a journey on the first five stations. Whether this assumption is mathematically and practically valid needs to be further verified. Another limitation of this project's work was that the number of station had to be limited to avoid track sharing with the Orange Line.

Future work on this project would include developing a way to incorporate more stations on the Silver Line that are shared with other lines. This would require additional constraints to prevent collisions and calculate overall travel cost. Other improvements to this project that could be made are simplification of the code to speed up the algorithm. This could be accomplished through the use of specialized libraries or even vectorization (if possible) to speed up the process of iterating through many loops. In addition, more factors such as delays could be accounted for in the model to increase its realism. The effect of this would be higher computation times, but given that this is not a real time skip stopping model, it would likely not be a significant hurdle for a train system operator.

References

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