Fastest Path Analysis in a Vehicle-to-Infrastructure Intelligent Transportation System Architecture

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Abstract – **In this paper, I perform an analysis of the time to traverse shortest paths compared to the time to traverse fastest paths as determined from a vehicle-to-infrastructure (V2I) architecture. Vehicle tracking devices have been installed in 15 vehicles that frequent the University of Alaska, Anchorage on a daily basis. This data has been fed into FreeSim (http://www.freewaysimulator.com) to determine the fastest path from the university to a location on the other side of the city. Two different vehicles traversed the fastest path and shortest path, respectively, each day of the week to determine the actual amount of time to traverse the paths. Although the fastest path did prove to be faster the majority of the time, there were some days for which the shortest path was ultimately faster than the calculated fastest path. I provide an analysis of these paths and analyze reasons as to why this may be the case.**

I. INTRODUCTION

Many intelligent transportation system (ITS) applications being developed assume that the ITS architectures have access to vehicle location, speed, and direction data. Different architectures have been proposed for capturing this data, including vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), and vehicle-to-vehicle-to-infrastructure (V2V2I) [1]. In a V2I architecture, vehicles transmit their speed, location, and direction data through a roadway infrastructure to a central computing facility. From this data, a representation of the roadway network can be determined, and ITS applications can leverage this data for their own uses.

Many ITS applications are currently being developed, such as incident identification, accident avoidance, congestion improvement, driver alertness, and fastest routing of individual vehicles, among other applications. Determining the fastest path from a vehicle's current location to its desired destination is one application that has been attempted using existing technologies, such as loop detectors and other means of gathering data at discrete locations [2]. Using a continuous flow of data, such as that gathered by individual vehicles that report their speed, location, and direction through a V2I architecture, the fastest paths for vehicles can be more accurately determined. Shortest path algorithms can be adapted to be fastest path algorithms by representing the weights of the edges by speed. Dynamic fastest path algorithms have also been created, which optimize the graph by taking into account underlying properties, such as the static nature of the graph structure by the constantly changing weights of the edges. A good description of these and other algorithms, as well as their running times and code, is provided in [3].

Although these algorithms have been tested in a simulated environment, they have not yet been tested in a live environment with real data gathered through a pure V2I network. In [4], the data used for the analysis was interpolated as continuous from loop detector data, though no study has actually used live distributed data in an analysis.

In Anchorage, there are currently 15 vehicles containing tracking devices that transmit speed, location, and direction data to a central server. This data is then used to determine the fastest path from a vehicle's current location to its desired destination. Although 15 vehicles are not enough to fully cover the entire city of Anchorage, the vehicles that contain the devices frequent the University of Alaska, Anchorage, which provides relatively accurate data of traffic flow conditions around the university at the times the vehicles are commuting (generally between 7:30a.m.-8:30a.m. and 4:30p.m.-5:30p.m.). For this study, the afternoon rush hour was used as a test case, with 13 of the vehicles able to travel along any path desired, and the remaining two vehicles traveling each day from the university to a predefined destination across the city. One of the vehicles took the shortest path each day and the other took the fastest path as determined by current traffic conditions and historical data from the same day of the week for the previous four weeks. The results are presented in this paper, organized as follows. Section II contains a brief description of related work. Section III explains the devices that were installed in vehicles and the vehicles into which they were installed. Section IV provides an analysis of the data that was gathered as related to fastest paths, and the conclusion is provided in section V.

II. RELATED WORK

Vehicle-to-vehicle (V2V) [5] and vehicle-to-infrastructure (V2I) [6] intelligent transportation system architectures have been widely studied in literature. The two architectures were combined into the vehicle-to-vehicle-to-infrastructure (V2V2I) architecture in [1], and vehicular ad-hoc networks (VANETs) are becoming increasingly more popular [7]. The means by which speed is determined from gathering data discretely at loop detectors is widely used by departments of transportation and was originally proposed in [8].

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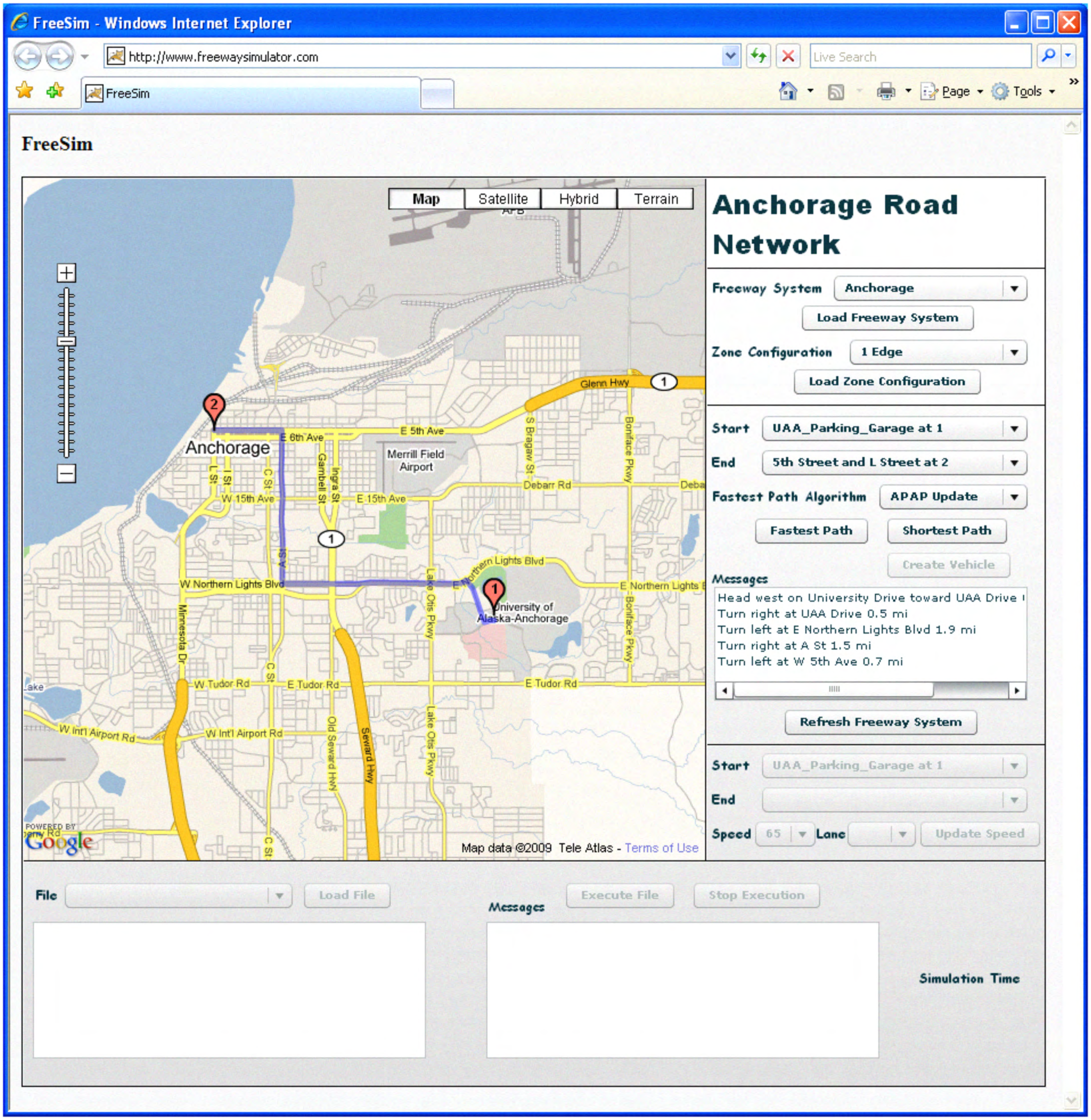
FIGURE I. FREESIM SCREENSHOT WITH SHORTEST PATH FROM SOURCE TO DESTINATION



Using ITS data, many applications have been proposed, such as incident identification, trip planning [9], characterization of traffic flows [10], and traffic prediction [11, 12], among others. It is impossible to enumerate all of the potential applications that could arise from the use of this data, though many traffic simulators exist that attempt to allow researchers to test their algorithms and traffic planning ideas on simulated data. FreeSim [13-15] is one simulator that does this, though the manner in which data is entered into FreeSim can be discrete or continuous, simulated or real, offline or real-time. An overview of simulators, including FreeSim, is provided in [15].

Shortest path algorithms in graphs have been studied for many years, with popular algorithms from Dijkstra [16], Bellman-Ford [17, 18], and Johnson [19]. Dynamic shortest path algorithms (which are used for graphs that have constantly updating edge weights, including adding and removing edges) have been studied by Demetrescu and

TABLE I. AVERAGE AMOUNT OF TIME TO TRAVERSE SHORTEST AND FASTEST PATHS ON EACH DAY OF THE WEEK BETWEEN OCTOBER AND DECEMBER 2008

Day of Week	Actual Time to Traverse Shortest Path	Calculated Time to Traverse Fastest Path	Actual Time to Traverse Fastest Path
Monday	17:32	15:06	15:32
Tuesday	17:16	15:05	15:39
Wednesday	17:37	16:18	17:05
Thursday	18:05	17:04	17:42
Friday	18:10	16:27	17:28

Italiano [20], as well as Miller and Horowitz [3], who took dynamic shortest path algorithms to the intelligent transportation system application. Changing the weights on the edges to represent speed will allow any of these algorithms to be used to calculate fastest paths instead of shortest paths.

With all of these algorithms and applications, the data used was either gathered at discrete locations (from devices such as loop detectors or video cameras) or the data was simulated to be continuous. More recent projects, such as MIT's CarTel [21] and UC Berkeley's Mobile Millennium [22] projects, are gathering data in a distributed manner from cellular phones, though no data has yet been published from these projects. Further, there is an additional challenge of trying to determine if the cellular device is actually located within a vehicle when it is transmitting the speed and location. A company called Airsage [23] has attempted a similar project in the Washington DC area. At the University of Alaska, Anchorage, the vehicles have dedicated vehicle-tracking devices installed, so there is no issue in determining which devices are communicating from vehicles. In addition, it is possible to strategically place the devices in vehicles that cover the city on a daily basis and minimize the amount of data necessary to be transmitted to a central infrastructure to maintain an accurate representation of the transportation network.

III. VEHICLE TRACKING OVERVIEW

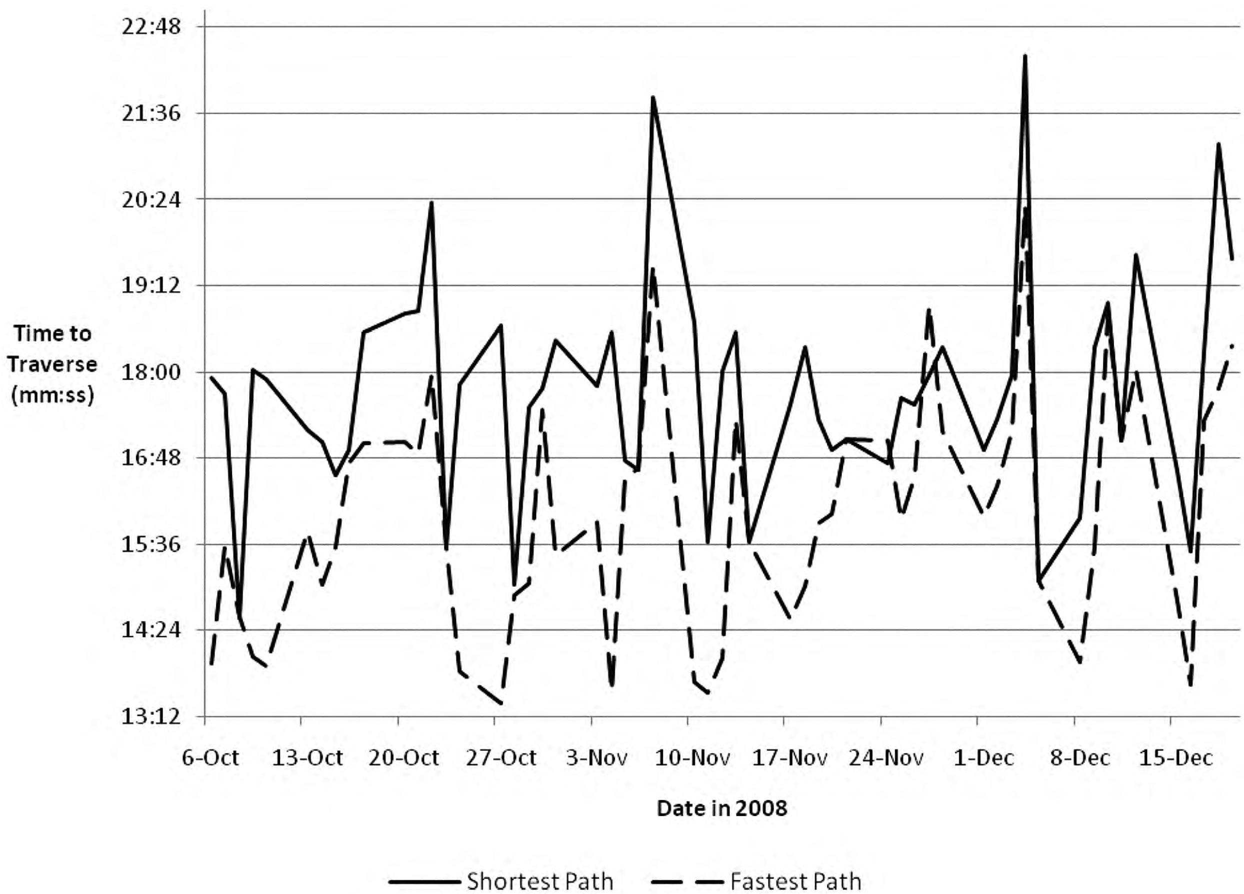
To ensure the data received by the central server contained accurate speed, location, and direction data from a vehicle while the vehicle was moving, individual vehicle tracking devices were installed in 15 vehicles. An RTV5 tracking device from Live View GPS [24] was installed in each vehicle, which contains a GPS receiver and a cellular transmitting/receiving antenna. The device transmits speed, location, direction, ignition status, the number of GPS satellites that are in view, and a unique identifier. If there are fewer than four GPS satellites in view, the data is not transmitted as there is a high probability of inaccurate location data at that point. Over a cellular link, this data is transmitted every 10 seconds (though this can be configured to communicate every five seconds or one second) to a central server, where it is stored in a database. If the device is unable to communicate over the cellular link, the data will be buffered until it can be transmitted. The data is exposed via a web site offered by Live View GPS using Microsoft Virtual Earth [25], and for the purposes of this study, the data is also fed directly into FreeSim, which is used for the simulation and to determine fastest paths at different times using current and historical data. FreeSim's interface uses Google Maps [26] to show the paths and the locations of all of the vehicles that contain the tracking devices. A screenshot of the FreeSim interface is provided in Figure I.

Since 15 vehicles are not enough to fully cover the city of Anchorage and provide speed data for the entire transportation network at all times of the day, the vehicles that contain the devices were strategically chosen as ones that frequent the University of Alaska, Anchorage and travel across the city around 5:00p.m. each weekday. The shortest path, including the source node and destination node, is provided in Figure I. The shortest path is 4.6 miles and takes 13 minutes and 39 seconds at speed limit with no traffic and average duration of stopping at the traffic signals. Thirteen of the vehicles did not have any limitations on the directions they were required to drive. One of the remaining vehicles always had to traverse the shortest path from the source to the destination, and the other remaining vehicle had to traverse the fastest path each day. The fastest path was determined by taking the vehicle data from the past four weeks for that specific day of the week at 5:00p.m., as well as the data that was already reported for the current day by the other vehicles. For example, to determine the fastest path for Monday, December 22, 2008, the vehicle data from November 24, December 1, December 8, December 15 were averaged together, then weighted with the current data for December 22. The fastest path was determined immediately before the vehicle left the university, which was around 5:00p.m. each weekday. The fastest path vehicle would then take that fastest path, with the actual amount of time to traverse the path tracked by the vehicle tracking device and reported through the V2I architecture to the central server. The shortest path vehicle also contained a vehicle tracking device that reported the actual amount of time to traverse the path it took through the V2I architecture to the central server. Section IV contains an analysis of this data.

IV. FASTEST VERSUS SHORTEST PATH ANALYSIS

Figure I shows the source and destination points that are used in the fastest and shortest path computations for this study. Since there were only 15 vehicles used for this project, if there was no data for a specific section of the roadway, the speed limit was used. The data gathered was from October

GRAPH I. ACTUAL TIME TO TRAVERSE SHORTEST AND CALCULATED FASTEST PATH



2008 through December 2008. Since the previous four weeks were used in the fastest path calculations, the fastest path became more accurate during November and December, since more historical data was able to be used. The average times for each day of the week at 5:00p.m. for the actual shortest path, actual fastest path, and calculated fastest path are provided in Table I. As can be seen, over time, the calculated average amount of time to traverse the fastest path is relatively close to the actual amount of time to traverse the fastest path, and the actual amount of time to traverse the fastest path is less than or equal to the actual amount of time to traverse the shortest path. At speed limit with average delays due to traffic signals, the 4.6 mile shortest path would take 13 minutes 39 seconds.

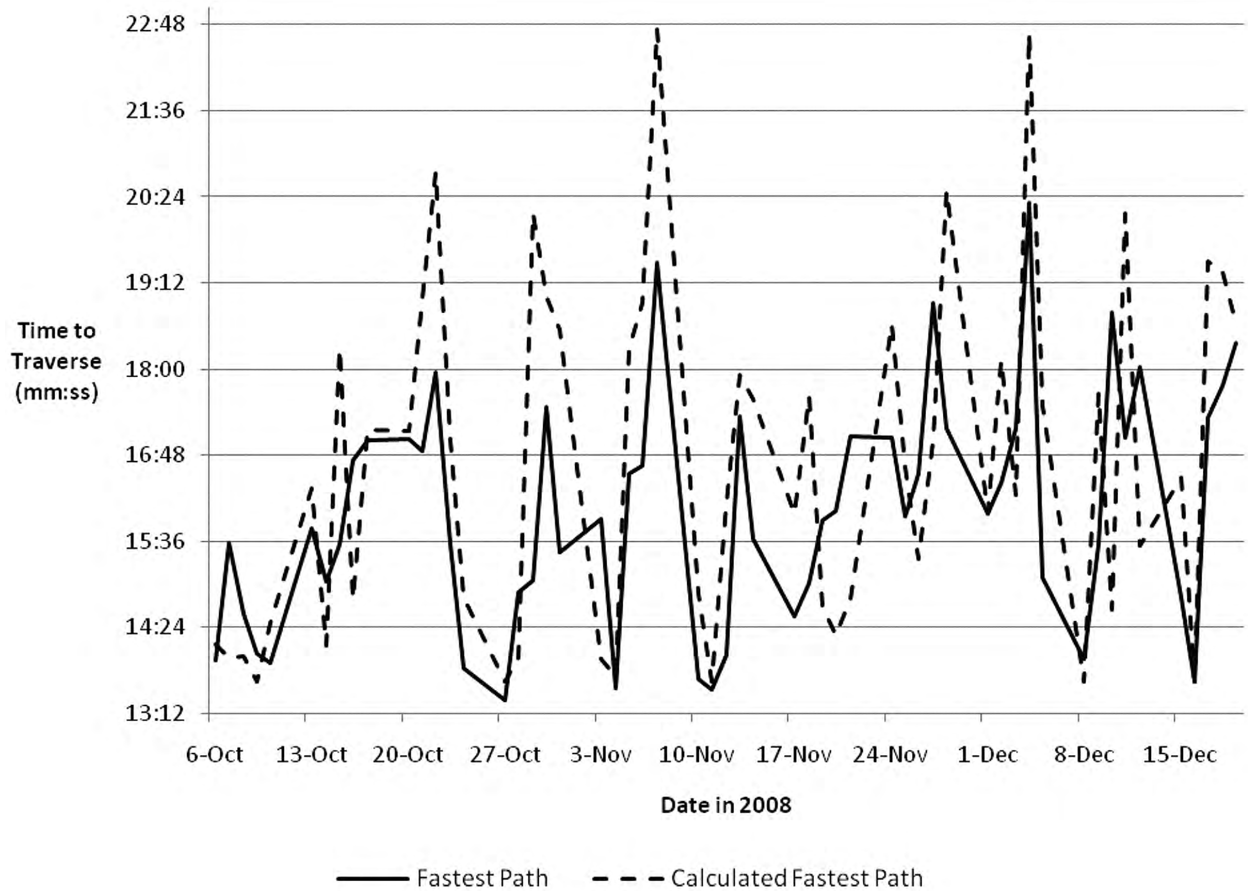
Graph I shows, for each day, the actual amount of time to traverse the shortest path compared to the actual amount of time to traverse the calculated fastest path. The shortest path does occasionally become faster than the actual amount of time to traverse the computed fastest path, which shows that the number of vehicles currently being used is not quite sufficient for accurately representing the transportation network. Further, driving conditions could have changed by the time the vehicle reached that point in the path, since the vehicle was not being updated with fastest paths while its location was changing. However, the computed fastest path is actually faster than the shortest path 84% of the time and faster or the same as the shortest path 96% of the time. These percentages show that even with a small number of vehicles being tracked, strategically placing the vehicle tracking devices can allow a large savings in commute times to be experienced.

Graph II shows the amount of time that was calculated for the fastest path compared to the actual amount of time to traverse it. Although accurate on some days, other days show that the driving conditions changed substantially before the vehicle traversed the path. Given updated fastest paths while a vehicle is traversing a path and more vehicles with tracking devices would improve this problem.

V. CONCLUSION

This study is one of the first to use live distributed data as gathered through vehicle-tracking devices to analyze traffic flow. The data was gathered from 15 vehicles in the Anchorage area that frequent the University of Alaska, Anchorage on a daily basis. Each day around 5:00p.m., the vehicles leave the university, which provides for realistic traffic conditions around the university. Two of these vehicles had specific tasks when leaving the university. One of the vehicles traversed the shortest path from the university to a predefined destination. Another vehicle traversed what was calculated immediately before departing as the fastest path

GRAPH II. ACTUAL TIME TO TRAVERSE CALCULATED FASTEST PATH VERSUS CALCULATED TIME TO TRAVERSE FASTEST PATH



from the university to the same predefined destination. The calculation of the fastest path was based on historical data from the same day in the previous four weeks, as well as the data from the other 13 vehicles for the current day. If there was no data for a specific section of the transportation network, the speed limit was used. This may have provided inaccurate data, since just because one of the 15 vehicles containing a vehicle tracking device was not on that section of the roadway tells nothing about the flow of traffic on that road. Further, the vehicle traversing the calculated fastest path was not receiving any updates in the middle of the commute, so if the fastest path changed based on changing traffic conditions, the vehicle traversing the calculated fastest path was not alerted to the change. Even with these two potential problems in calculating the fastest path, the results of this study were encouraging. The calculated fastest path actually took less or the same amount of time as the shortest path 96% of the time, and the fastest path took less time than the shortest path 84% of the time.

In the future, I will be installing the vehicle tracking devices in more vehicles in the Anchorage area. I will also be utilizing vehicle fleets that already have tracking devices installed, such as delivery companies, taxi fleets, buses, and emergency response vehicles. With more vehicles reporting speed, location, and direction data, the fastest paths will be much more accurate. In addition, I am already working on an application to report fastest paths to vehicles while in transit based on their current locations, which will better account for changing traffic conditions.

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