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TRAFFIC SIMULATION APPLICATION TO PLAN REAL-TIME DISTRIBUTION ROUTES

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ABSTRACT

This paper studies the effect of real-time information on optimal routes employed by distribution vehicles that supply goods from distribution centers to the stores in any retail environment. This methodology uses simulation models to mimic actual traffic conditions as functions of times of the day along the distribution routes to suggest meta-optimal routes over the ones provided by the routing algorithms. This yields optimized routes based on the times of the day in addition to aiding the planner in sequencing the routes to increase driver productivity and decrease operating costs.

1 INTRODUCTION

Recent studies have shown that drivers in the largest 68 metropolitan areas in the nation spend on average 40 hours per year stranded in traffic. The trend is also alarming, in less than 20 years there has been an increase of 150 percent in the annual number of hours that a driver wastes sitting in traffic. In small urban areas the impact has been even larger, with congestion growing 300%. All this has negative consequences not only for passenger car driver suffering the increasing urban and sub-urban congestion, but also for businesses that rely on the surface transportation network to operate.

In this paper we study the effect of traffic congestion on distribution routes. The methodology presented here uses traffic simulation models to determine traffic conditions (travel time and average speeds) as function of the time of the day along the distribution routes. This information is used to optimize not only departing times so that the total travel time on a route is minimized, but also to develop strategies that allow a combination of several routes to increase driver productivity and decrease operating costs.

Distribution routes are typically used by transportation vehicles (trucks) to deliver products to multiple stores in a given area. These stores are usually supported by a distribution center (DC) that is designated for those stores. Trucks start from a DC, replenish multiple stores, and then come back to the DC either empty or with some backhauls (returns or defective products from stores). Optimal routes are typically computed using routing and scheduling software. The goal of this paper is to improve upon the suggested routes using real-time traffic information by integrating these routing suggestions with simulation models.

This paper is organized as follows. Section 2 provides the methodology developed for improving the routing using real-time information. Section 3 provides the simulation results and findings of this study. This if followed by Section 4 that has a discussion of results. Finally, we present our conclusions and recommended future work.

2 METHODOLOGY

The problem studied here involves one distribution center and 15 stores located within a geographical area covering approximately 1,000 sq. miles in Kentucky. The 15 stores were assigned to four routes (3 four-shop routes and 1 three-shop route) which were select by an off-the-shelf routing optimization software package.

To study the effects of traffic congestion on departing times and travel time for the distribution routes, we simulated an actual transportation network south of Lexington, KY. The network included two towns —Richmond and Berea— separated approximately 15 miles and connected by Interstate 75 and several state highways. Within these two urbanized areas, we considered major arterials and collectors, but not minors streets, to represent the transportation network.

Besides topological information, the traffic simulation model we used requires data about geometry and traffic channelization (i.e., number of through-traffic lanes, number of right- and left-turning traffic lanes); speed limit; type of traffic control devices and, where applicable, their settings (e.g., stop sign, yield sign, or traffic signal plus duration of its cycle and phases); and other traffic parameters. The demand on the network; that is, traffic volumes entering the network by time of the day, were obtained from Origin-Destination (O/D) information covering a period of time on a weekday from 5:00 AM to 12:00 PM that served as input to traffic assignment models. Those traffic assignment models "assign" traffic to different paths between a given origin and destination, taking into account the congestion levels along those possible paths.

All this information was input to a macroscopic traffic simulation model, named OREMS, developed at the Oak Ridge National Laboratory (see Franzese et al., 1998). Once the traffic simulation was run, the model produced aggregated results, such as average speed and travel time, for each segment of highway and arterial in the network by time of the day. For example, Figure 1 presents the travel time on a one-mile segment of a main arterial in Berea averaged over five-minute intervals. As shown in that figure, this segment of road becomes congested (i.e., operating at low average speeds and, therefore, longer travel times) during the period of time between 7:10 AM and 8:55 AM, due to a high traffic demand (i.e., commuters getting from the suburbs into the downtown area).

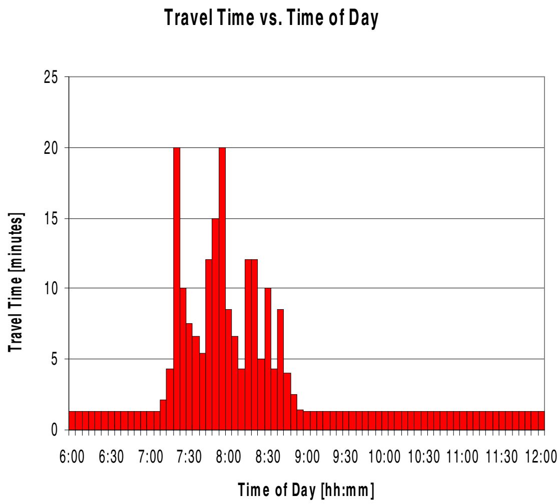

Figure 1: Average Travel Time on a Segment of a Main Arterial in Berea during the Morning Peak Hour

This information can be used to construct travel times from any origin to any destination in the network as a function of time. For example, a vehicle entering the arterial segment of Figure 1 at time 7:20 AM is expected to spend 20 minutes to travel from one end to the other. At the end of the 5 minute period, that car would have traveled ¼ of a mile. During the 7:25 to 7:30 AM period, the simulation indicates that the average travel time on the link is 10 minutes; so at 7:30 AM the position of the car would be ¾ miles downstream from the segment starting point. During the next time interval the simulation predicts an average travel time of 7.5 minutes, with which the car would reach the end of the arterial segment at 7:31:52 AM. Therefore, the total travel for a vehicle entering the segment of arterial under consideration at 7:20 AM would be 11 minutes and 52 seconds. The same vehicle entering the arterial segment at 6:20 AM would have reached its end in 1 minute and 20 seconds traveling at 45 mph (the arterial speed limit).

Using this procedure, it is possible to determine the travel time on any given path of the network as a function of the starting time of the trip. The procedure can also be easily expanded to include stop times, making it suitable to schedule distribution routes such that the total travel time is minimized.

3 RESULTS

We used the methodology described above to compute travel times for the four routes considered in this paper. Each routed started at the distribution center, located east of Berea, and served 3 or 4 stores which were located in Berea, Richmond, and in a area east of Richmond. We first computed the shortest path for each one of the routes using the methodology, but without considering any stops. Figure 2 shows the six shortest paths for Route 1. Path # 6 was selected for further analysis since for any given starting time, it always provided the lowest travel time (i.e., it dominated all other alternatives for Route 1). We proceeded in the same fashion for the other 3 routes.

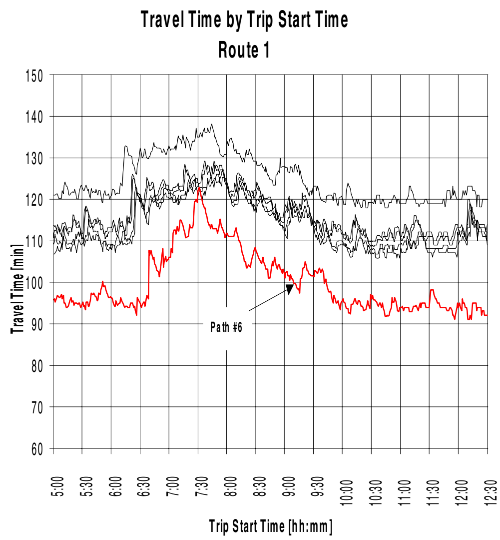

Figure 2: Travel Time for the Six Shortest Paths of Route 1 vs. Departing Time from the Distribution Center

These routes were generated using Manugistics routing and scheduling software, TRUCKS™. These routes may not necessarily follow the shortest path as was considered by the simulation model. All stores that are served by a distribution center are considered and then optimal routes are generated subject to a maximum number of stops per route. The maximum number of stops considered for this paper was 4. Although this software has the capability of scheduling routes based on time windows of the stores and also other parameters, the constraint of time windows was not incorporated for this study.

To compute the total route distribution time we assumed a deterministic 15 minute stop time to model the unloading/loading time at each shop. Note that this is a parameter to the simulation model and can be changed depending upon the specific application. For example, in retail this time is typically much higher, say in hours, but for fast-food delivery trucks, the unloading time may be about 30-45 minutes. The simulation model is independent of these times, since these times can be changed and the results can be re-analyzed. Selecting a starting time from the distribution center, we computed the travel time to the first shop using the methodology described before. Since we assumed a 15 minute stop time at the stores, the departing time from the first shop was then the arrival time plus 15 minutes. This departing time was used to compute the travel time to the second shop; 15 minutes were added to the arrival time to the second shop to compute the departing time to the third shop, and so on until the trip was completed (i.e., arrival time to the distribution center). The difference between the arrival time at the distribution center at the end of the route and the departing time from the distribution center at the beginning of the route was then assigned as the travel time associated to that particular the departing time for the route.

Figures 3 to 6 show the travel time for each of the 4 routes (using the corresponding shortest paths) as a function of the departing time from the distribution center. The horizontal line in the graphs indicate the travel time considering no congestion (i.e., traveling at the speed limit on each link in the path).

These routes were computed from the Manugistics Routing and Scheduling software TRUCKS™. The network was created using latitudes and longitudes of the stores and Distribution Center considered in this study.

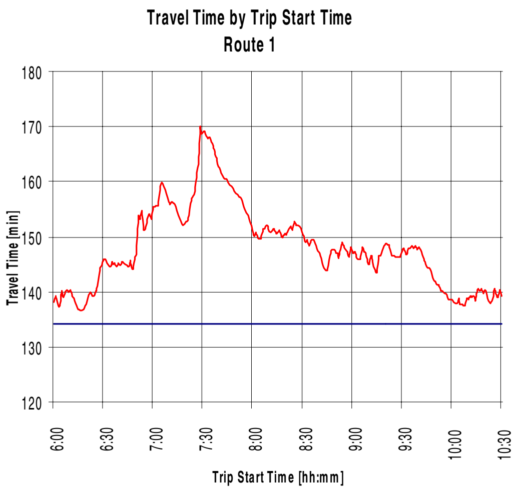

Figure 3: Travel Time vs. Departing Time for Route 1

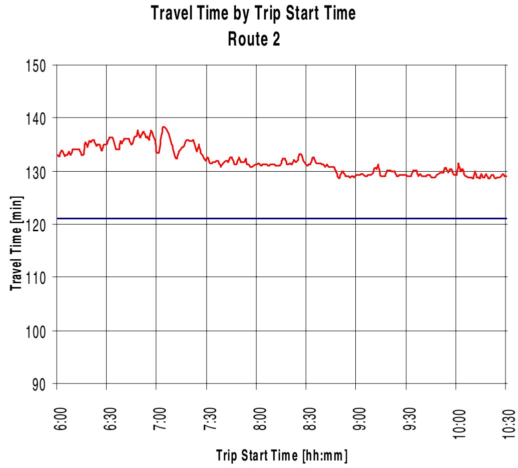

Figure 4: Travel time vs. Departing Time for Route 2

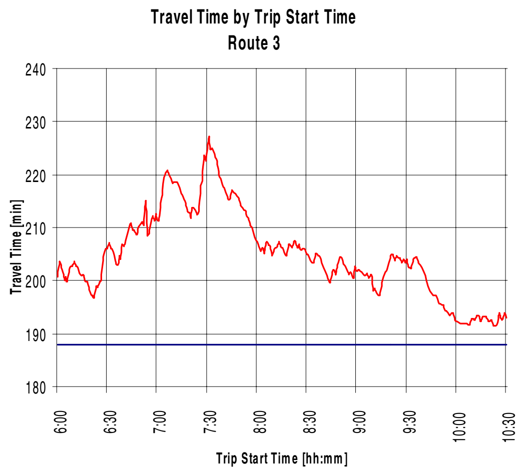

Figure 5: Travel Time vs. Departing Time for Route 3

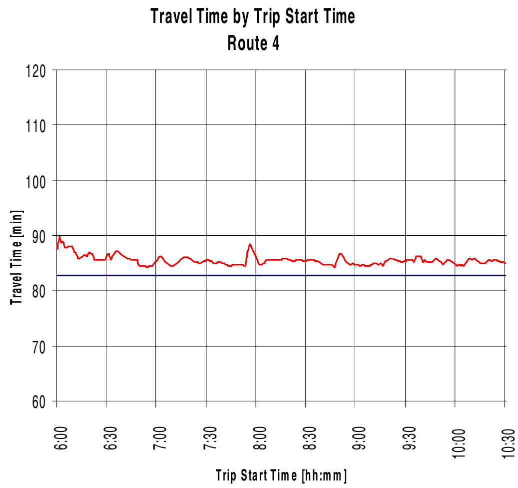

Figure 6: Travel Time vs. Depart Time for Route 4

The demand at all stores was assumed to be the same. This network was considered for the purpose of this paper only and has no significance to any real life operation of any DC or stores.

4 DISCUSSION

The results of this study, although based on few routes on a particular transportation network, suggest that the role that congestion play in determining the optimal distribution routing cannot be neglected. Two distinct cases emerged from the traffic simulation we performed. The first one, what we call a low-reliability travel time or LRtt case, correspond to Routes 1 and 3 (see Figures 3 and 5). This is a case in which travel time varies considerably with the departing time. Distribution routes that fall under this case are highly sensitive to the time at which the trip starts. For example, starting Route 1 at 6:15 AM instead of at 7:30 AM can reduce total travel time on that route by 33 minutes (i.e., 169 min – 136 min), or 19.5% of the total travel time.

The second condition, a high-reliability travel time (HRtt) case, is illustrated in Figures 4 and 6 corresponding to Routes 2 and 4, respectively. For routes that fall under this category, the departing time does not have a significant effect on the total travel time. For example, the difference in travel time for Route 2 between departing at 7:05 AM (worst departing time for this route) or at 9:30 AM (best departing time) is only 9 minutes, or 6.5% of the total travel time.

These two distinct route characteristics can be combined to optimize operations at the distribution center by reducing the total travel time across routes. For example, a driver departing at 6:00 AM for Route 3 would return to the distribution center at 9:20 AM. If that driver departs at 9:25 AM for Route 4, then the total time to serve both routes would be 4 hours and 50 minutes, since he/she would be back at the distribution center at 10:50 AM. However, if the order of the routes is reversed (i.e., Route 4 is served first and Route 3 second), then the total time to serve the same 2 routes would increase to 5 hours and 17 minutes (assuming, as before, a 5 minute stop at the distribution center between the end of the first route and the start of the second). This 27 minute increase not only reduces driver productivity but it also increases operation costs since during this extra 27 minutes the truck will be consuming gas (and also increasing pollution).

The determination of whether a route will a HRtt or LRtt route cannot be made with currently available models that simply rely on geographical information (i.e., network topology) and some information about the characteristics of the network (e.g., type of roads, speed limits, etc.). Even knowing the network traffic demand by time of day (i.e., the number of trips from all the points in the network where traffic originates to all the points that attract traffic) and feeding that information to traffic assignment models is not enough to determine the operational characteristics of the network (e.g., link travel times and speeds). This is because the traffic controllers at each intersection in the network (e.g., stop signs, yield signs, traffic signals) play a key role in the overall level of capacity that the network has. For example, even under uncongested conditions (e.g., early morning departing times), travel times on the network with simulated traffic are always higher than those obtained under the assumption that it is possible to travel at the speed limit along all links on the route. This is illustrated on Figures 3 to 6, on which the horizontal line in the middle of the graph (which represents free-flow travel time for the specific route) is always below the travel times obtained from the simulation. The difference is due to traffic controllers along the route that would stop traffic even if the demand on the perpendicular streets is null. The consequence of these stops is a decrease on the overall speed along the route which can only be determined with a simulation model or with real-time information about traffic flows on the network.

5 CONCLUSIONS

Currently available models cannot provide the detailed information needed to schedule distribution routes since those models do not take into account the congestion that may arise on a transportation network due to demand peaks. In this paper we have suggested a simple methodology to optimize distribution routes by using traffic simulation models which can provide in depth information about traffic conditions on a network. Our methodology uses this information to construct travel times as function of time of the day to identify the shortest path for a given route, and to combine routes to optimize the overall operations of the distribution center.

In our methodology we have assumed fixed stop times at the stores, but this assumption can be easily relaxed. Moreover, the methodology lends itself to determining the length of these stop times (over the minimum time required to accomplish whatever tasks need to be carried out at the stores) such that the total travel time on the route can be minimized. That is, in some cases it may be better to wait at the shop longer than required just to avoid "riding" the congestion. The simulation model can provide the necessary information to make this determination.

This paper focused on "recurrent congestion"; that is, congestion that develops on a network simply due to the relationship between the traffic demand and the available capacity of the network. However, simulation models allow the study of other type congestion —i.e., non-recurrent congestion— which originates as consequence of incidents such as crashes, road maintenance, road construction, and other events. Our methodology can be easily expanded to incorporate this information to study the effects of incidents on the distribution routes travel times.

Simulation models, by their very nature, are data intensive and this has been, and is, the major obstacle to their use in traffic modeling. One way to reduce the number of simulation replications and achieve the same level of confidence (variability) is to apply variance reduction techniques (see Chapter 11 of Law and Kelton for an elegant introduction to variance reduction techniques) . These can be appropriately introduced in these class of simulations so that the simulation run-times are optimized. Also, new technologies —the so called Intelligent Transportation Systems or ITS— are being deployed across the nation that make it possible to determine and collect traffic conditions (see report by FHWA ITS Joint Program Office, 2000). This information, together with advances in remote sensing technologies (see both Franzese and Xiong, 2001) that permit road recognition and attribution can be used to supply the necessary inputs to traffic simulation models.

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