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Potential Effects of Automatic Vehicle Location and Computer-Aided Dispatch Technology on Paratransit Performance

A Simulation Study

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Automatic vehicle location (AVL) and computer-aided dispatch (CAD) systems have afforded a unique opportunity for public transit agencies to integrate these technologies in their paratransit systems for improved productivity and reliability. This opportunity has also prompted widespread interest in quantifying the benefits that can be attained from such technological enhancement. This research assesses the potential effects of AVL and CAD on the productivity and service reliability of a paratransit system. A simulation model that can realistically model AVL and CAD functionality is used in the investigation. Many cases representing variations in operating environment, such as service area, demand intensity, and proportion of real-time demand trips, are simulated for a sensitivity analysis under three assumed operational improvements—en route diversion, dwell time reduction, and periodic reoptimization. The results indicate that although AVL and CAD effectiveness varies from case to case, on average, these systems can help to substantially improve paratransit performance.

Operation of a dial-a-ride paratransit service requires a mesh of interrelated managerial functions, such as trip reservation, vehicle monitoring, scheduling and dispatching, and business reporting. Each of these functions can potentially be made more efficient and reliable with the support of advanced information technologies such as computers, automatic vehicle location (AVL), and telecommunications (*1–5*). For example, telecommunications systems enable constant link among customers, vehicle operators, and dispatchers, who therefore can respond promptly and effectively to any changes in system conditions. AVL systems enable continuous monitoring and tracking of fleet vehicles and their schedules, providing dynamic scheduling with real-time information. Computer-aided dispatch (CAD) systems automate dynamic scheduling, such as inserting real-time demand trips into existing routes and reassigning scheduled trips among routes, offering the opportunity for increased productivity and reliability. Although these potential benefits have been widely recognized, little evidence is available on their potential magnitude. The objective of this research is to conduct a systematic investigation of the effectiveness of AVL and CAD in improving the productivity and reliability of dial-a-ride paratransit systems.

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Research on quantifying AVL and CAD benefits was first initiated by Wilson et al., who performed an extensive simulation study with various operational assumptions on systems with and without AVL (*6, 7*). That research concluded that, on average, a 10 percent increase in vehicle productivity could be expected by using a continuous location system. The dial-a-ride systems studied were real time, and all trips were assumed to be same-day, immediate requests. Latest developments in intelligent transportation systems have generated a renewed interest in evaluating the cost-effectiveness of technologies and numerous field studies have been conducted for regular transit and paratransit (*8–10*). Hardin et al. conducted a field study of a paratransit service provider in Miami, Florida, on AVL potential in improving paratransit productivity (*11*). The study found that AVL technology was not particularly useful in the selected application. However, significant benefits could have resulted if real-time information provided by AVL had been adequately used in the management process. Recently, Higgins et al. reported a 10.3 percent increase in vehicle productivity from using AVL technology and advanced scheduling systems on Houston Metro's paratransit service (*12*). Although a field study is valuable in providing firsthand experience, it also has many limitations, including difficulties in transferring experience between different sites because of the interdependence between system performance and underlying operating conditions, and in isolating benefits attributable to specific technology components. Further, a field study is often constrained by the scheduling system of the paratransit provider, which may not have the functionality required for taking advantage of real-time information (*5*).

An overview is presented of the methodology applied in the comparative analysis, focusing on how systems with and without AVL and CAD are modeled. The results of a series of simulation experiments are described, to identify the relationship between the potential AVL and CAD benefits and underlying operating conditions. Finally, conclusions and future research directions are highlighted.

METHODOLOGY

To compare the relative performance of systems with and without AVL and CAD, a simulation system, SimParatransit, is used to generate data required for the analysis. SimParatransit is a simulation model developed specifically for evaluating advanced paratransit systems under various operating conditions, technology options, and dispatching strategies, as described by Fu in this Record, pp. 93–99. The modeling methodologies applied in SimParatransit are as follows:

- Simulation of the detailed activities of individual vehicles in service, starting from accepting their assigned routes and schedules, to moving from street to street along the shortest path, to picking up or dropping off customers. The street network in the service area is explicitly modeled, with time-dependent, stochastic travel speed on individual roads.
- Modeling of various real-time events, including late vehicles, real-time requests, trip cancellations, and dispatcher-related events such as periodic schedule reoptimization.
- Interactive simulation (dispatching) under which a user can act as a dispatcher and make dispatching decisions in response to computer-generated, real-time events.
- Explicit modeling of AVL and CAD functionality. The simulation system models AVL as the means for a dispatcher to access the coordinates of service vehicles and models CAD with a set of dynamic scheduling functions.

Although AVL technology provides vehicle location data in real time, it is the dynamic scheduling component CAD that uses the available data to improve system productivity and reliability. In SimParatransit, the AVL and CAD functionality is modeled with regard to additional operational flexibility and information that these technologies could provide, including en route diversion, reduction in dwell time, and periodic reoptimization.

En Route Diversion

A primary CAD function is to determine how to assign real-time demand trips to vehicles already in service with a given set of routes and schedules. The SimParatransit simulation model extends the dynamic assignment algorithm from the algorithm for the static version of dial-a-ride problems with a set of modified objective functions and constraints (*13*). The algorithm can be summarized as follows:

- The dynamic assignment algorithm finds an insertion that minimizes the total additional cost from the insertion. The additional cost is defined as a weighted combination of the cost to the service provider (total service time) and total disutility to existing and new clients. The disutility to clients is represented by waiting time and excessive ride time. For clients already on schedule (advance reservation trips), waiting time is defined as the difference between the promised arrival time (arrival time scheduled before service starts) and the expected arrival time after the insertion. For real-time demand trips, waiting time is defined as the difference between the request time and the scheduled pickup time. Excess ride time is extra ride time compared with a customer's direct ride time (without any diversion to other customers).
- The scheduling algorithm must consider a set of operational constraints, including seating requirements, vehicle availability, pickup and drop-off time windows, and maximum allowable waiting and ride times. For schedule validity, the scheduling process guarantees that the number of customers on each vehicle does not exceed the capacity of each seating type at each stop along the route. For real-time demand trips, the time window is simply determined on the basis of request time and maximum allowable waiting time, whereas for advance reservation trips, absolute latest pickup and drop-off times need to be considered.

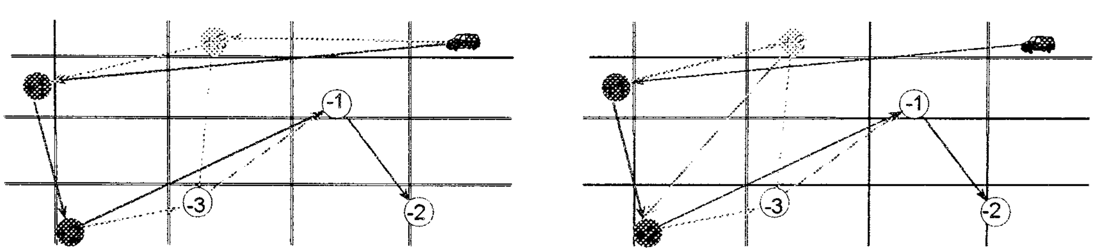
An AVL system is modeled differently from one without AVL on the basis of two operational assumptions, similar to Wilson et al. (*7*):

1. In an AVL system (Figure 1*a*), each vehicle that is traveling to the next stop according to its schedule may be diverted en route by the dispatcher to pick up a new client. Such a diversion is made only if is efficient and does not adversely affect service to existing clients.
2. Conversely in a system without AVL (Figure 1*b*), the location of each vehicle is not always known by the dispatching center. The assumption is that a vehicle is not diverted from its immediate destination for a new client. However, a diversion is allowed after the first stop along the route, because the location of that stop is known to the dispatcher.

The model is biased somewhat to overestimating the efficiency of systems without AVL, because it assumes the systems without AVL have some type of dynamic scheduling and communications ability. As a result, a comparison based on this en route diversion model should be considered only when comparing systems with AVL and CAD and ones with CAD only.

Reduction in Dwell Time

A second effect of AVL and CAD systems is a potential decrease in the time required for a vehicle to pick up a customer. The basic premise is that if customers can check the real-time location of AVL-equipped vehicles and their expected pickup time (e.g., via the Internet), they could get ready for travel before the vehicles arrive. This means that the dwell time at pickup stops may be reduced for a system with AVL and CAD. SimParatransit enables the user to



(a) (b)

FIGURE 1 Dynamic scheduling: (*a*) with AVL; (*b*) without AVL (trips 1 and 2: advance reservation trips; trip 3: real-time demand trip).

specify the mean and variance of dwell times for individual trips and thus the analysis of dwell time reduction effects.

Periodic Reoptimization

By tracking individual service vehicles (AVL) and dynamically updating schedules (CAD), vehicle schedules can be reoptimized periodically for more efficient and reliable operations. Such a reoptimization capability is especially attractive in an operating environment subject to large variations because of factors such as real-time requests, trip cancellations and no-shows, and time-varying traffic congestion. These variations would likely result in conditions that deviate substantially from the conditions assumed when schedules were prepared or dispatching actions were performed. Reoptimization may take place on three increasingly complex levels—(*a*) rescheduling the times of a fixed route (sequence of stops on the route is to be maintained), (*b*) resequencing the order of stops on a route, and (*c*) reassigning trips from one route to another. From a theoretical point of view, the benefits attainable from reoptimization should increase as the scale and frequency of reoptimization increase. However, frequent changes in vehicle schedules may cause problems for dispatchers, drivers, or even clients, and therefore may not be acceptable in practice even if technologically feasible. Therefore, a reoptimization strategy, removing and reinserting (RR) algorithm, has been devised, whose objective is a controllable balance between maximizing reoptimization benefits and maintaining the stability of operating schedules.

The basic idea of the RR algorithm is to sequentially remove individual trips on each route and then try to find the best way to reinsert them back on the routes. The following is the general procedure of the algorithm:

1. Select vehicle (route) k from the fleet, and do the following:
   a. Select trip i that is yet to be picked up by vehicle k, and do the following:
      (1) Remove trip i from route k and update its schedule.
      (2) Find all feasible ways in which trip i can be inserted into vehicle k. Keep the minimum insertion cost (C_k) and the associated schedule. If it is not feasible to insert trip i into vehicle k, set C_k = INFINIT.
      (3) Find all feasible ways in which trip i can be inserted into each of the remaining vehicles of the fleet. Find the vehicle (r) that results in a minimum insertion cost. Keep the minimum insertion cost (C_r) and the associated vehicle and schedule. If it is not feasible to insert trip i into any of the remaining vehicles, set C_r = INFINIT.
      (4) If C_k - C_r > D, select vehicle r for inserting the trip i or else select the same vehicle (k) for the trip i.
   b. If there are still trips left to be examined, $i = i + 1$ and go back to *a.*
2. If there are still routes left to be examined, $k = k + 1$ and go back to 1. Otherwise, stop.

Note that the RR algorithm includes a parameter Δ that can be used to control the flexibility allowed in alternating existing schedules during reoptimization. Using a large Δ value implies that priority is given to maintaining schedule stability. Another parameter associated with reoptimization is the time interval in which RR is invoked during simulation. Consequently, the RR algorithm effectiveness depends on these two parameters, and optimal parameter values may be identified via an extensive computational simulation analysis. Finally, the results from the RR algorithm depend on the order in which the vehicles (routes) are selected for reoptimization. In the current implementation, vehicles were selected in a descending order, from the earliest to the latest insertion in RR.

SIMULATION EXPERIMENTS AND RESULTS

Results are presented of the simulation experiments conducted to examine the difference in paratransit operational performance between systems with and without AVL and CAD. The experiments were performed using a set of hypothetical cases and a real-life example.

The hypothetical cases were generated on the basis of the following specifications:

1. Two service areas—10 km^2 and 20 km^2. Each area is covered by a uniform-grid road network, with all neighboring nodes (intersections) connected by two links, one in each direction. Each link is 500 m long and the travel speed is 30 km/h. The scheduling algorithm uses rectangular distance and a travel speed of 30 km/h to calculate travel time.
2. Trip origins and destinations are uniformly distributed over the service area with desired pickup or drop-off time uniformly distributed within the 2-h service period from 7:00 to 9:00 a.m.
3. For each case, trips are divided into two groups according to a given percentage—advance reservation trips and real-time demand trips.
4. The fleet vehicles are assumed to be identical, with a seating capacity of 10 passengers and unlimited fleet size fleet.

The real-life example consists of a weekday off-peak service covered by the Disabled Adult Transportation System in Edmonton, Alberta, Canada. Two cases were used—460 trips for the off-peak period (11:00 a.m. to 1:00 p.m.) and 570 trips for the afternoon peak period (3:00 to 5:00 p.m.). To model real-time demand trips, the original list of trips was divided into reservation trips and real-time demand trips. The original trip database did not include the dwell time required at each trip stop; therefore a 1-min dwell time was added to each pickup and drop-off stop. A fleet of vehicles, each with 10 seats, provides the service. In scheduling, travel times between stops are estimated on the basis of rectangular distance and an average travel speed of 30 km/h. The road network includes all arterial streets and freeways in the service area. Travel time on each link was assumed to be deterministic on the basis of the posted speed limit associated with the link. Although the hypothetical scenario assumes a uniform distribution of trips over a service area, the Edmonton cases represent more realistic situations in which trip clustering is taken into account.

The routing and scheduling objective in both static and dynamic scheduling was assumed to minimize total travel time only. A maximum 90-min ride time and a maximum 30-min service time deviation were used in scheduling the reservation trips. In real-time dynamic scheduling, the maximum waiting time was 30 min for demand trips and 10 min for reservation trips. These constraints define the minimum level of service that must be guaranteed for each test case. Note that in all tests, an unlimited fleet with a large seating capacity was used to eliminate the effect of capacity constraints and the possibility of any trip rejection. Thus, the vehicle productivity measure can be approximately used as the sole criterion in comparing system costs for different scenarios.

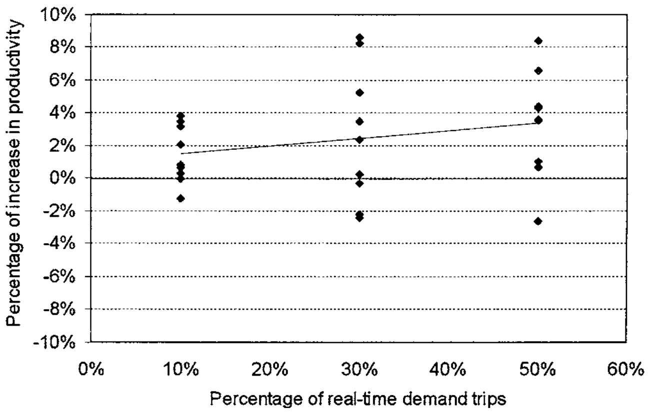


FIGURE 2 Relationship between productivity improvement from en route diversion and proportion of real-time trips (service area: 10 km²; hypothetical cases with trip density = 0.5 to 1.5 trips/h/km²)

Benefits from En Route Diversion

AVL benefits that may accrue from en route diversion are identified. The hypothetical operating environments were first used for the sensitivity analysis. Three levels of demand with trip densities of 0.5, 1.0 and 1.5 trips/h/km² (corresponding to a total of 100, 200, and 300 trips, respectively), were considered, with the percentage of demand trips varying from 10 to 50 percent. At each demand level, three random sets of trips were generated to represent the variation in trip distribution. Each trip was assumed to have a 1-min pickup and drop-off dwell time. No travel time variation was considered, and the periodic reoptimization was not applied in this analysis. Each case was simulated twice—once with AVL (allowing en route diversion) and once without AVL. The resulting statistics were compiled for further analysis.

Figure 2 shows the relationship between the percentage increase in productivity from en route diversion and the percentage of demand trips in the 10 km² service area. Three observations can be made from these results. First, AVL systems have a clear advantage over systems without AVL as far as vehicle productivity. The average increase in vehicle productivity ranged from 1.7 to 3.5 percent, with 8.8 percent as the highest observed increase.

Second, the relative increase in productivity appears to be an increasing function of the proportion of demand trips, with an approximate 1 percent productivity improvement, on average, for every 20 percent increase in demand trips. This relationship is somewhat expected, because the higher the real-time demand, the more opportunities for en route diversion and thus the more advantageous it is for an AVL system.

Third, the benefit is highly case dependent, with productivity improving from 2.5 to 8.8 percent. For 5 out of 27 cases, a decrease in productivity was observed, indicating that AVL had adversely affected system performance. Such performance variation is expected, however, because the relative advantage of an AVL system depends on the formation and location of the active routes and demand trips. Some combinations have better potential than others for travel time savings using en route diversion. Further, in a dynamic system, a decision made at the present affects the future state of the system. As a result, whereas a dynamic assignment solution is advantageous to an AVL system under current conditions, it may be less desirable in the future when other demand trips are added.

Productivity also improved in the real-life example of Edmonton, Alberta, for three hypothetical real-time trips, as shown in Figure 3. The average productivity increased from 2 to 4 percent for off-peak hours and from 5 to 7 percent for the afternoon peak hours.

Productivity improvement from the en route diversion strongly correlates with the size of the service area and trip density, as shown in Figure 4. This result was obtained in simulating the two service areas under three different levels of trip density, a fixed proportion of demand trips (20 percent), and a link travel time coefficient of variation (COV, defined as the standard deviation divided by the mean) of 0.2. Two patterns can be clearly identified. First, for a given service area, the average productivity increased as the trip density increased, which is expected as higher trip density means more diversion opportunities. Second, as far as improved productivity, en route diversion is more beneficial in larger than in smaller service areas. The average productivity increase was as

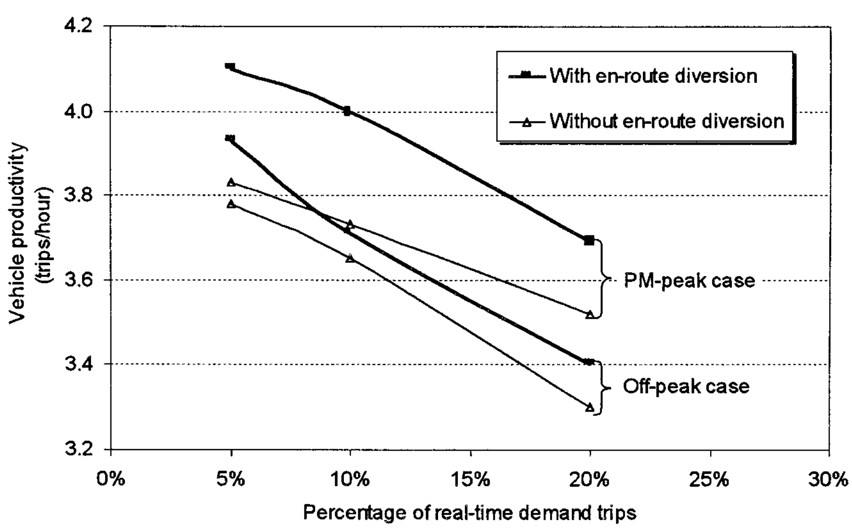


FIGURE 3 Relationship between productivity improvement from en route diversion and proportion of real-time demand trips (Edmonton cases).

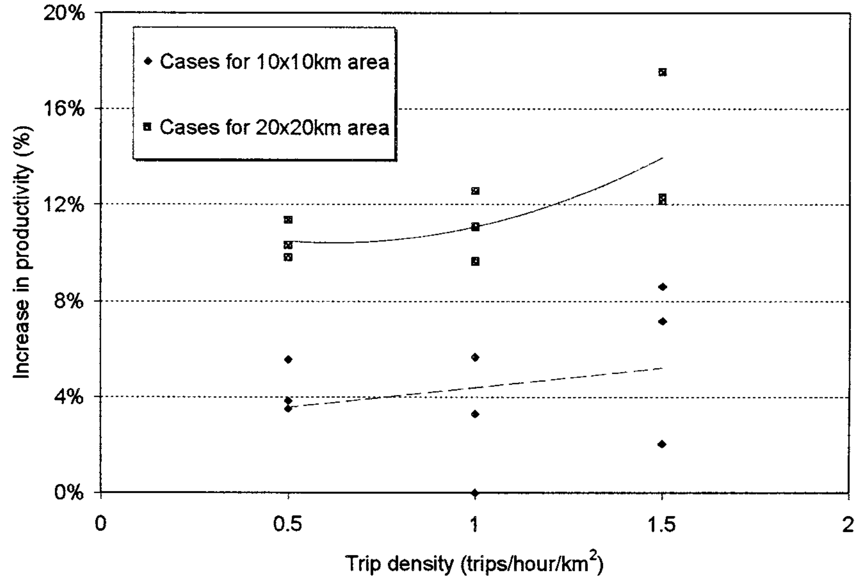


FIGURE 4 Relationship between productivity improvement from en route diversion and trip density (demand trips = 20 percent, COV = 0.2).

high as 12 percent for the 20 km^2 area and only 4 percent for the 10 km^2 area.

Finally, a noticeable advantage appears evident as far as system efficiency using en route diversion for any given percent of demand trips, productivity decreases as the proportion of demand trips increases (Figure 3). This finding seems to indicate no overall benefit results from accepting real-time requests. However, the benefit from accepting real-time trips should be considered with regard to improved customer convenience and a potential reduction in trip cancellation, as discussed by Fu in a paper in this Record.

Benefits from Reduction in Dwell Time

One possible effect of AVL and CAD on paratransit operations is the potential to reduce the time a vehicle stops when picking up a customer. The objective of this section is to analyze the potential effect of this hypothetical AVL and CAD effect on the productivity of a paratransit system is analyzed. Simulations were performed on the hypothetical cases generated at three levels of trip density (0.5, 1.0, and 1.5 trips/h/km^2) in the 10 km^2 service area and for the Edmonton off-peak hours of operation. Each case included 20 percent of demand trips and no travel time variation. Also, each trip was assumed to have a drop-off dwell time of 2 min and a pickup dwell time of 4, 3.5, 3, or 2 min.

Figure 5 presents the simulation results. Curves represent the relationship between the improvement in productivity and percentage reduction in pickup dwell time. Compared with the results from dynamic scheduling, the potential benefit generated by AVL and CAD from reduced dwell time is much more substantial. A small change in dwell time from 4 to 3.5 min (12.5 percent reduction) increased productivity by more than 5 percent. An improvement of more than 10 percent could be attained if the pickup dwell time were reduced by 25 percent (from 4 to 3 min). The simulation results of the Edmonton off-peak cases show productivity increases of 4 and 6 percent, respectively.

Benefits from Periodic Reoptimization

The objective of periodic reoptimization is to revise preestablished schedules in response to changes in system conditions. Any benefits from reoptimization can be expected to depend on the magnitude and frequency of variability in system conditions. Empirical evidence is presented that was obtained from simulation experiments with variations resulting from travel time and real-time requests. The simulations were performed for the 10 km^2 area, with each case having 200 trips generated at a trip density of 1.0 trips/h/km^2. The interval for reoptimization was set to 30 min, which was identified as an appropriate value after a set of test runs. The reoptimization parameter Δ was set to zero, meaning that the reoptimization algorithm considered only the travel time benefit and did not consider the maintenance of schedule stability. The en route diversion function was applied for all cases with reoptimization, and vice versa.

The system variation by adding real-time demand trips is first considered. Cases with a different percent of real-time trips were

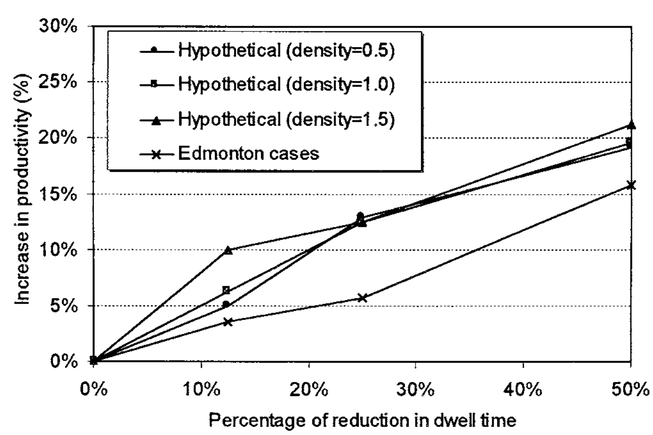


FIGURE 5 Relationship between increase in vehicle productivity and reduction in pickup dwell time.

simulated in a deterministic network. Figure 6 shows the relationship between the increase in vehicle productivity (relative difference in vehicle productivity between systems with and without periodic reoptimization) and the proportion of real-time trips. Although system productivity is generally a decreasing function of the percent of real-time trips with and without reoptimization, the relative benefit from reoptimization increases as the variation in system conditions, represented by the percent of real-time requests, increases. The relative improvement in vehicle productivity from reoptimization was 4 percent with no real-time trips and increased to as high as 25 percent with 30 percent real-time trips. Note that some improvement may stem from the en route diversion capability when scheduling real-time requests.

The effects of travel time variations on paratransit performance are next analyzed. Simulated cases had different levels of link travel time variability, as represented by the COV ranging from 0.0 to 0.3. To isolate the effects caused by travel time variation, no real-time trips were considered in this analysis. Figure 7 shows the relative increase in vehicle productivity due to reoptimization as a function of link travel time COV. It is interesting to observe that the relative benefit due to reoptimization was insensitive to link travel time variation, which somewhat contradicted intuition. One explanation for this result is that, while the real-time reoptimization function can take advantage of knowing the current locations of the service fleet, it does not gain any additional accuracy in travel time estimates as compared to the cases without reoptimization. If estimates on travel times could be improved in real time and used in the reoptimization process, improved vehicle productivity could be expected (*5*).

In terms of quality of service to clients, periodic reoptimization was found to have noticeable benefits and the benefits were strongly correlated to the travel time variability. Figure 8 shows the means and standard deviations of pickup and drop-off lateness under the scenarios of with or without periodic reoptimization as functions of link travel time COV. As expected, with an increase in COV, the average lateness and the variation of the lateness also increased; consequently, the benefit of real-time reoptimization also increased.

CONCLUSIONS

This study was conducted to quantify the potential benefits of paratransit systems with AVL and CAD. A simulation model capable of representing these technology components was applied. Many cases representing variations in operating characteristics, such as service area, demand intensity, and percent of real-time trips. The simulation results provide the following insights:

1. The effectiveness of AVL and CAD systems strongly depends on the operating environment and on how information made available with AVL and CAD is used. The implication of this finding is that conclusions from limited case studies should be taken cautiously for any generalization.
2. In view of the anticipated level of real-time demand likely to be accepted by paratransit agencies in the near future, the AVL benefit resulting solely from en route diversion seems to be limited. The simulation results show that the average increase in productivity was less than 4 percent, although increases exceeding 8 percent were also observed. Decreased productivity was also found for a few simulation cases, implying that increased efficiency may not always result from using AVL.
3. If AVL and CAD can help reduce customer dwell time, significant benefits may be realized. More than a 10 percent productivity improvement could be attained if the pickup dwell time were reduced by 25 percent.
4. Significantly improved productivity is attainable if AVL and CAD can be used in implementing real-time, periodic reoptimization of vehicle schedules. The simulation experiments showed that the relative improvement was closely related to the proportion of real-time trips and was less related to travel time variation. Also, real-time reoptimization was benefited clients by improving on-time performance, and the relative benefit was highly correlated to travel time variability.

Finally, the simulation analysis performed in this study is limited in representing diverse operating conditions (e.g., size and shape of service area), service policies (e.g., maximum ride deviation and response time), and dispatch strategies (e.g. form and frequency of reoptimization). More extensive research is therefore needed before any definite generalizations can be made.

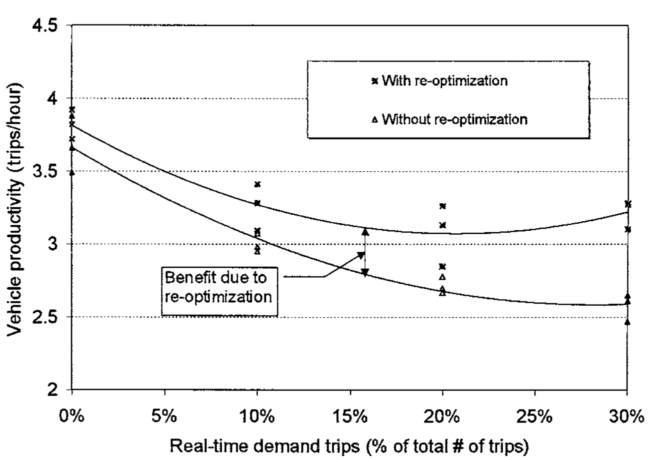


FIGURE 6 Relationship between increase in vehicle productivity from periodic reoptimization and proportion of real-time trips.

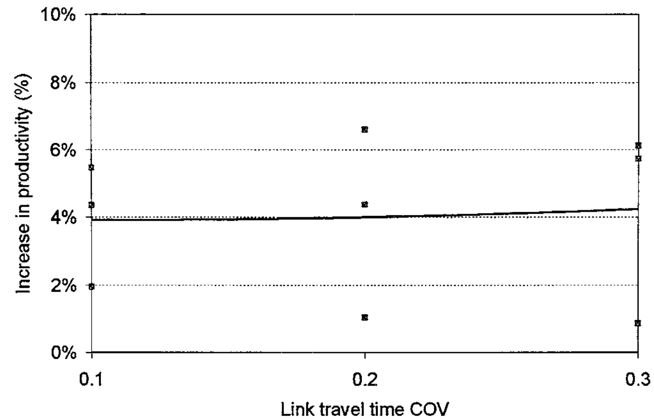


FIGURE 7 Relationship between increase in vehicle productivity from periodic reoptimization and link travel time COV (demand trips = 0 percent).

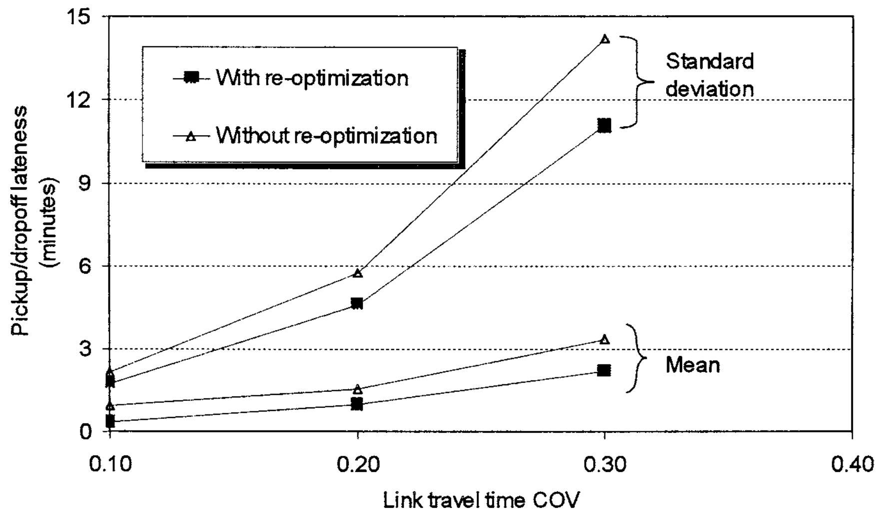


FIGURE 8 Relationship between pickup/drop-off lateness with and without reoptimization and link travel time COV (demand trips = 0 percent).

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