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Simulation model performance analysis of a multiple station shared vehicle system

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Abstract

As an alternative transportation paradigm, *shared vehicle systems* have become increasingly popular in recent years. Shared vehicle systems typically consist of a fleet of vehicles that are used several times each day by different users. One of the main advantages of shared vehicle systems is that they reduce the number of vehicles required to meet total travel demand. An added energy/emissions benefit comes when low-polluting (e.g., electric) vehicles are used in the system. In order to evaluate operational issues such as vehicle availability, vehicle distribution, and energy management, a unique shared vehicle system computer simulation model has been developed. As an initial case study, the model was applied to a resort community in Southern California. The simulation model has a number of input parameters that allow for the evaluation of numerous scenarios. Several measures of effectiveness have been determined and are calculated to characterize the overall system performance. For the case study, it was found that the most effective number of vehicles (in terms of satisfying customer wait time) is in the range of 3–6 vehicles per 100 trips in a 24 h day. On the other hand, if the number of relocations also is to be minimized, there should be approximately 18–24 vehicles per 100 trips. Various inputs to the model were varied to see the overall system response. The model shows that the shared vehicle system is most sensitive to the vehicle-to-trip ratio, the relocation algorithm used, and the charging scheme employed when electric vehicles are used. A preliminary cost analysis was also performed, showing that such a system can be very competitive with present transportation systems (e.g., rental cars, taxies, etc.).

Keywords: Shared vehicle system; Station car; Intelligent transportation systems

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1. Introduction

It has been estimated that congestion in the US causes travel delays costing the public over US$100 billion annually (Euler and Robertson, 1995). Further, traffic congestion leads to high levels of vehicle emissions, resulting in severe air quality problems in many metropolitan areas. Solutions to private vehicle congestion have been sought for many decades. Current public transportation systems such as buses can to a certain degree alleviate congestion, however they lack the flexibility and convenience of privately owned vehicles. On the other hand, taxis offer a higher degree of convenience, with the trade-off of high cost. What is needed is a public transportation system that offers the effectiveness and low cost of mass transit, and the flexibility of individual vehicles.

As an alternative transportation paradigm, *shared vehicle systems* have the potential to make metropolitan regions much more livable by reducing the number of vehicles within a community, thereby relieving congestion and associated air pollution and fuel consumption. Shared vehicle systems can take on many forms (e.g., see description in Shaheen and Nerenberg, 1998), but the general idea is that individual vehicles are not privately owned, but are shared by several users making different trips throughout the day. This inherently reduces the number of vehicles required for given travel demand and also reduces parking requirements.

Car sharing organizations (CSOs) are a common form of the shared vehicle concept which are becoming rather prevalent in Europe and Canada (see, e.g., LeFond, 1994; CarSharing Portland, 1998; Glotz-Richter, 1998; Cooperative Auto Network, 1998; Mobility, 1998; Shaheen et al., 1998). A CSO is an organization that provides shared-use vehicles to its members on a short-term rental basis. The CSO user pool typically consists of people within a constrained community or who share a common large employer or activity-base. Users typically reserve a vehicle for a specific trip, and at the time of the trip they obtain the vehicle keys from a common lock box. They then use the vehicle for a short period of time, after which they return the vehicle, recording their mileage. At the end of the month, each user gets billed a standard fee plus a mileage-based charge. The CSOs are successful because they fill the gap when public transportation, walking, or cycling are not adequate, and the cost of operating a private vehicle is too expensive. Many CSOs estimate that each car-sharing vehicle replaces approximately 5–10 private vehicles, thereby reducing air pollution and fuel consumption (Glotz-Richter, 1998).

The *station car* concept is a slightly different form of a shared vehicle system (see, e.g., Shaheen and Nerenberg, 1998). Station car systems are typically associated with larger mass transit systems such as rail (see, e.g., National Station Car Association, 1998; New Jersey PowerCommute Project, 1998; Atlanta Georgia Station Car Demonstration, 1998). Vehicles are owned by a transit district or a third-party service provider and are dispatched out of transit stations primarily for use by transit riders. In this case, a traveler "rents" a station car primarily to and from their home and "home" station, and/or to and from their work place and "work" station. Errand trips are also possible around the station. As with CSOs, the station cars can be reserved in advance or be made available to walk-up travelers. Because the trip distances of a station car are rather short, the vehicles can be small and low-polluting, e.g. electric vehicles. The electric vehicles can be recharged while parked at the transit stations.

In recent years, there has been a tremendous amount of activity in *Intelligent Transportation System* (ITS) technology and in clean vehicle propulsion systems (e.g., electric vehicles, hybrid electric vehicles, compressed natural gas, etc.). Shared vehicle systems can benefit greatly from both of these areas:

ITS technology. Numerous "smart" technology bundles have been defined within a common ITS framework (see Euler and Robertson, 1995), many of which are applicable to shared vehicle systems. Intelligent communication and reservation systems exist to provide vehicle location identification, vehicle tracking, dispatching, and reservations from several sources (web, phone, kiosk, etc.). On-board navigation and travel information can also assist within a shared vehicle system, and smart-card technology can be employed for vehicle access control. All of this ITS technology can make a shared vehicle system more efficient, easier to manage, and far more friendly to the users. An example of demonstrating what ITS technology can be applied to a shared vehicle system is described in Chisholm (1996). In their Instant-Rent-A-Car (IRAC) research (no longer operational), the main focus was on the technologies required to have the entire system function independently, including GPS-based localization, cellular telephone communication, vehicle access, and in-vehicle processors. The Praxitele shared vehicle system also employs a high degree of ITS technology (Augello et al., 1994).

Clean vehicle propulsion. Shared vehicle systems have the potential to replace many private vehicles and can have further significant environmental benefits if low emitting vehicles are used. Low emitting vehicles, e.g., electric vehicles, are very well suited for shared vehicle systems. The trips made by shared vehicle systems are typically shorter than for a private vehicle (particularly for station cars), since they are constrained to trips around town and are not used for long-haul commutes or vacations. Electric vehicles have very low total emissions but they still suffer from limited range. The range matches well with the short travel distances of a shared vehicle system, and electric vehicles can take advantage of opportunity charging at their holding locations. Naturally, electric vehicles in a shared vehicle system operating on standard roadways must meet Federal Motor Vehicle Safety Standards (FMVSS).

Members of CSOs and users of station car systems predominantly make round trips when using the shared vehicles. In CSO, a user typically rents a shared vehicle to perform an errand, e.g., going to the store for groceries. The shared vehicle trip originates and ends in the same spot. For a station car system that is tied into a mass transit mode such as rail, round trips are also the norm (although recently, multi-port one-way trips are becoming possible, see below). A user gets off the train near home, rents a station car to go home, and returns the vehicle back to the station the next morning. A "reverse" commuter may then arrive at the same station, rent the same vehicle to go from station to work, then returns the vehicle back to station at the end of the day after work is over. Shorter term errand trips also begin and end at the station. These are all considered roundtrips, i.e., users start and end at the same location.

Another slightly different form a shared vehicle system is one in which users rent shared vehicles between *multiple* stations. An example of this is when a shared vehicle system is set up in a resort or recreational area, or perhaps in a popular downtown area. Multiple stations are located at places of high activity, e.g., airport, major hotels, shopping areas, etc. A user may arrive by plane at the airport, and rather than renting a rental car for the duration of the stay, instead uses the shared vehicle system. A shared vehicle is used to get from the airport to the hotel. Later in the day, another shared vehicle may be rented to go to the golf course. Roundtrips will still occur in this type of system, however there will be a large number of one-way trips made between the multiple stations.

The reason that this distinction is made between predominantly round-trip shared vehicle systems (RTSVS) and multiple station shared vehicle systems (MSSVS) is that operating an MSSVS is much more difficult than operating an RTSVS. The problem is that with an MSSVS, the system can quickly become imbalanced with respect to the number of vehicles at the multiple stations. Due to uneven demand, some stations during the day may end up with an excess of vehicles whereas other stations may end up with none. Therefore, it is important to have a *vehicle relocation mechanism* that moves vehicles from station to station in order to bring the system back into balance, and users can still be satisfied at all stations. With an RTSVS, all the stations will have a finite number of vehicles and the system will never become unbalanced, therefore such relocation mechanisms are unnecessary.

An example of MSSVS is the Praxitele System being developed by a consortium of public transport operators, industrial manufacturers, and national research institutes in France (Augello et al., 1994). The Praxitele system is based on small electric self-service vehicles that are being applied to areas where traditional public transportation systems are not well adapted.

Within an MSSVS, there are several critical operational issues:

- *Vehicle availability*. The dominant operational issue centers on vehicle availability. If a user has to wait a long period of time to pick up and use a shared vehicle, it is likely he/she will not use the system, and the system will fail. On the other hand, an excess of vehicles is economically detrimental for the shared vehicle system owner/operators. Therefore, a balance must be achieved in order to have just enough vehicles operating within the system.
- *Vehicle distribution*. Another key issue centers on the distribution of vehicles. As previously mentioned, if the demand for vehicles among stations is asymmetrical throughout the day, some stations will tend to accumulate vehicles, while others will end up short of supply. In order to avoid these situations, a *relocation* mechanism must exist where a number of vehicles can be transferred from one station to another at critical times during the day. It is envisioned that such a relocation mechanism can be implemented using a car-carrying truck or platooning (towing) a set of vehicles from one station to another.
- *Vehicle energy management*. If the shared vehicles are electric, close monitoring of the battery state-of-charge (SOC) is critical. Various recharging schemes can be used at the stations and should be part of the shared vehicle system operation design.

In order to provide insight on these shared vehicle system operational and performance issues, we have developed and utilized a unique computer simulation model. The developed computer simulation model is a queuing-based, discrete event simulation which models each individual vehicle in the shared vehicle network over a specified period of time (typically 24 h). Vehicle "trips" are generated based on travel demand data. The model then implements specific charging schemes, relocation mechanisms, and trip time calculations that can be varied using different input parameters. Critical output parameters dealing with vehicle availability and distribution are then accumulated throughout the simulation and are analyzed after each simulation run. Other simulation models have been developed in the past to evaluate proposed car sharing operations (see, e.g., Liu et al., 1983) but not to such a high degree of detail.

As a case study, this model has been applied to a resort community in Southern California. Communities in Southern California's Coachella Valley have multiple factors that are well suited for a shared vehicle implementation. The region attracts a large number of visitors throughout the year, resulting in a high demand of temporary transportation (i.e., rental cars). The community is also already accustomed to the use of sub-compact electric vehicles (i.e., golf carts) in light of California Assembly Bill 110 (Golf Cart Transportation Plan, see California State Assembly Bill AB110, 1995). Also, the present business infrastructure of the area is supportive of such a system.

Section 2 of this paper briefly outlines the data collection process for the model, and the model itself. Section 3 then describes results of the model implemented for the resort community, which can be generalized to other shared vehicle systems. Also in Section 3 is a short cost analysis for the example resort community implementation. Major conclusions and future work are then discussed in Section 4.

2. Model development

2.1. System description

The shared vehicle system described here consists of several components, all of which take advantage of different kinds of ITS technologies:

2.1.1. Vehicles

Electric vehicles are the best candidate vehicles for shared vehicle systems since they are low-polluting and can take advantage of opportunity charging at the stations. The modeled vehicles can carry up to two passengers (possibly more) with ample room for luggage. On-board travel information is also provided for route planning as well as for identification of tourist attractions, shopping centers, etc. On-board telephones may also be provided. Smart-card technology is employed for access control.

Another key aspect of electric vehicles is that it is much easier to control and automate electric vehicles than conventional, internal-combustion-engine vehicles. Shared vehicle systems lend themselves well to automation, particularly when vehicle relocations are necessary. In the current system model, only a minimal amount of automation is realized.

2.1.2. Stations

In the model, shared vehicle stations are located at several key locations within the community. The vehicles are able to recharge when they are idle at the stations. Registration kiosks at the stations allow the users to interface with the system, primarily to request the use of a vehicle. Access control to a vehicle is done through a smart-card system with an appropriate personal identification number (PIN).

2.1.3. System operation center

The shared vehicle fleet is monitored at an operation center using automated vehicle location (AVL) technology such as GPS/cellular or radio frequency (RF) triangulation/signaling. By monitoring the location and state of each vehicle, the system operation center can run appropriate algorithms (see Section 2.3) to efficiently determine the redistribution needs of available vehicles among the stations.

2.2. Data collection

When modeling shared vehicle systems, conventional microscale transportation models are not appropriate for modeling specialized vehicle trips within a transportation network. Therefore, much effort was spent in developing a queuing-based discrete event model that has the appropriate characteristics of a shared vehicle system. When applying this model to the resort community, it was necessary to collect information on both the network geometry and the potential travel demand.

2.2.1. Network geometry

The first step in creating a transportation simulation model is to establish the system network for the area of interest. This consists of identifying the critical locations of stations that correspond to high levels of activity (e.g., airport, hotels, shopping, etc.) and routes between them. This can be accomplished using a combination of Geographical Information System (GIS) software and an instrumented vehicle equipped with Global Positioning System (GPS) technology. For the case study area, initially six stations were identified (shown in Fig. 1) based on travel demand reports generated by the Coachella Valley Association of Governments (CVAG). In addition to the identification of these stations of high activity, the routes between them were identified. The distances between stations as well as the trip durations were determined using GPS instrumented vehicle. The distance information is used directly by the model to calculate simulated trip durations. The measured trip travel times were used to establish ''friction factors'' for the routes between stations.

2.2.2. Travel demand data

One of the most important tasks in establishing the shared vehicle transportation model is estimating the travel demand between activity nodes. Typically, travel demand data is organized as trip origin/destination (O/D) matrices that are indexed by time of day (hourly), day of week, and week during the year. An O/D matrix simply contains the number of trips that are taken from an origin node to a destination node in a specified period of time. All combinations of nodes are represented in O/D matrix, and one matrix corresponds to a single time period.

Like many resort communities, our case study has several tourist seasons throughout the year. There is a peak season which corresponds to January through May, an off-peak season corresponding to June through October, and a mid-peak season corresponding to November through December. Also, the travel demand changes significantly for weekdays (e.g., Monday–Thursday) and weekends (Friday–Sunday). When running the model, all six different levels of travel demand were used (i.e., six combinations of peak, mid-peak, and off-peak with weekend and weekday). The total estimated number of trips in a 24-h period for each case is shown in Table 1.

Various sources in the region were used to establish the visitor travel demand data, including information from the local visitor bureau, the local association of governments, the airport authority, and many of the major hotels. Documents obtained throughout the area detailed visitor and resident travel patterns and preferences reasonably well. The majority of this data was based on surveys and questionnaires directly answered by individual visitors and residents. To minimize the effects of individual visitor/resident bias, and to create a more diverse database, additional surveys were performed throughout the year focusing on identifying potential user trends observed at each station. Based on the information gathered, six hourly indexed O/D matrices were

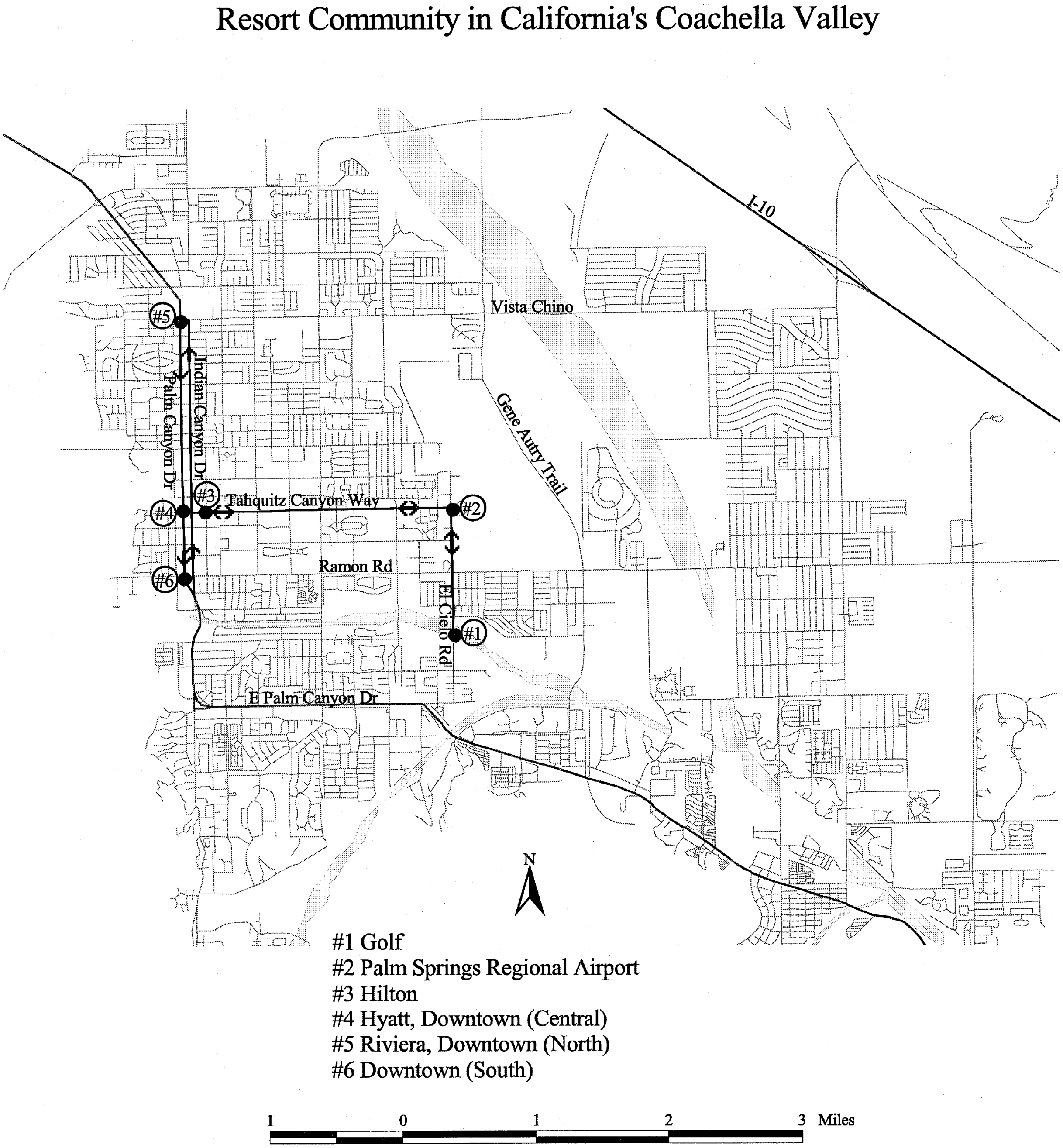


Fig. 1. Shared vehicle network layout for resort community in California's Coachella Valley.

created for the model, corresponding to the demand cases describe above. As an example of the travel demand variation throughout the day, Fig. 2 shows the diurnal demand for each station in the model implementation. The sum of all trips is also shown to detail the overall daily variation.

Table 1
Number of estimated trips in 24 h for each demand case

Total estimated trips	Peak (Jan–May)	Mid-peak (Nov–Dec)	Off-peak (Jun–Oct)
Weekend (Fri–Sun)	2261	1473	935
Weekday (Mon–Thurs)	1425	1063	666

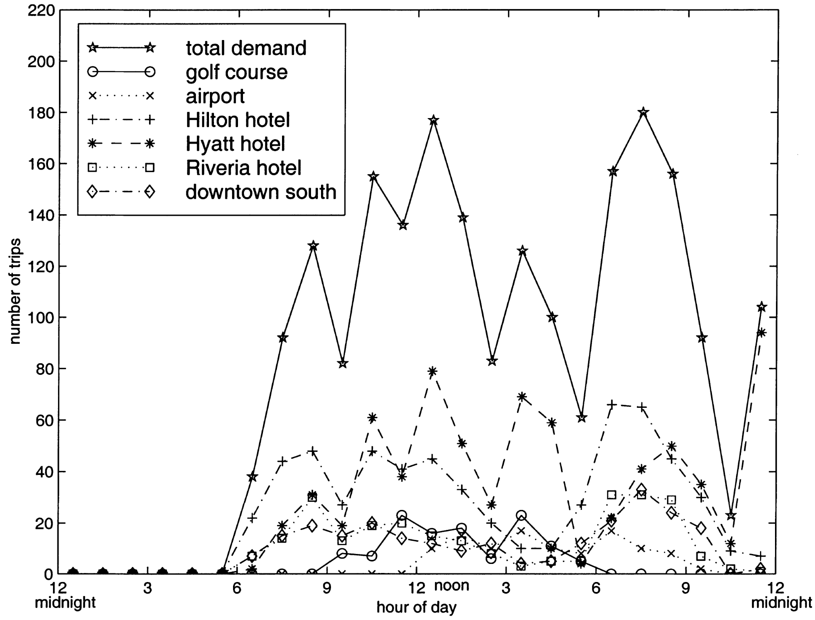


Fig. 2. Diurnal demand for individual stations and total.

2.3. Model implementation

2.3.1. General description

In order to evaluate the functionality of the resort community shared vehicle system, a queuing-based transportation simulation model was designed and developed. An overall block diagram of the simulation model is shown in Fig. 3. There are three major processing stages, i.e., (1) stochastically generating vehicle trips; (2) simulating the traffic on the network; and (3) evaluating the results with analysis/visualization tools. In order to generate trips, a *trip generator* program is used, described in detail in Section 2.3.2. The trip generator program uses the various O/D matrices as the primary data input. There is also a set of control parameters that adjust the behavior of the trip generating program. The output of the trip generator is a time-sequenced list of trips which is used as input to the next processing component, the *traffic simulator*. The algorithmic flow of the traffic simulator is described in Section 2.3.3. It has various input control parameters which affect the overall operation of the simulation. As the traffic simulator executes, a number of critical parameters are recorded which are subsequently evaluated using a set of *analysis tools*. In

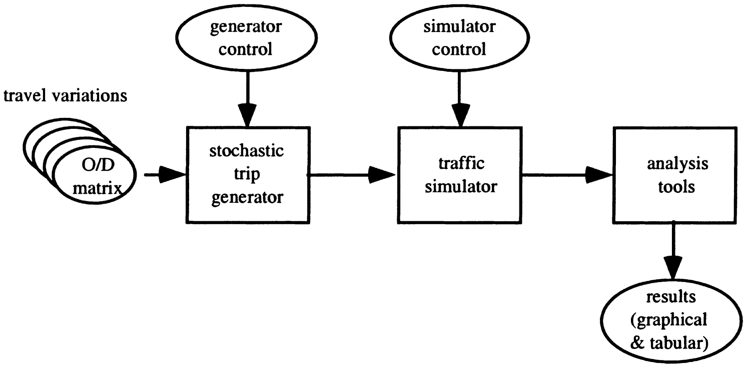


Fig. 3. Overall model block diagram.

addition, a visualization tool has been developed to illustrate the movements of the vehicles between the different stations. Specific results of the model are given in Section 3.

2.3.2. Stochastic trip generator

The stochastic trip generator reads in the origin–destination pairs contained in the input O/D matrix. The O/D matrix specifies the number of trips made from station to station on an hourly basis (note that round-trips, e.g., running an errand, are possible, originating and returning to the same station). From these hourly trip volume estimates, a *mean time between generation* (*mtbg*) value is calculated for each station pair, each hour. The *mtbg* value is calculated simply by dividing the number of trips into 60 min of an hour. Thus, *mtbg* represents the average time between trip generations (in minutes). Using the hourly *mtbg* data, vehicles are then spawned based on a modified Markov Process. In a normal Markov process, times between generations have an exponential distribution with infinite support. In order to avoid extreme behavior in the simulation, inter-generation times which are extremely high (above five standard deviations) are eliminated and the remaining sample is shifted accordingly.

The generation rate is given by:

$$T_{\text{next}} = -1.0349 \times \frac{\log(u) \times mtbg}{V_{\text{master}} \times V_{\text{hour}}},$$

where T_{next} is the calculated generation time, u is a uniformly distributed random variable between 0 and 1, *mtbg* is the mean time between generations for a specific origin/destination pair, V_{master} is a master volume factor, and V_{hour} is an hourly volume factor. Both V_{master} and V_{hour} are input control parameters to the trip generator program. The result of the trip generator is a stochastic, time-sequenced list of trips. Each trip is characterized by a generation time and a *from_node* and a *to_node* specification.

2.3.3. Traffic simulator

The main part of the model is the *traffic simulator* component. Trip information provided by the trip generator is used as input into the traffic simulator, which then simulates each vehicle trip on the given network for a specified period of time (typically for 24 h). The traffic simulator is a hybrid discrete-event and time-stepped simulation model, allowing for large network/vehicle size without loss of validity. It is based on the application of queuing theory to networks and features single vehicle level-of-detail.

The traffic simulator models the operation of a shared vehicle system as a collection of independent *processes* which interact with each other using coordination and communication structures. Functional components of a shared vehicle system, such as customers, station managers, and relocation controller are simulated as individual *processes*. Shared resources, such as vehicles, registration kiosks, and parking slots are treated as *facilities* within the simulation environment. The global system behavior is simulated as a collective effect of these numerous relatively simple, locally interacting components. Major *events* that have a significant effect on the overall system status and behavior are simulated in the model. Some examples of events include customer arrival at a station, vehicle departure from a station, vehicle arrival at a station, relocation start, relocation end, etc.

The general simulation algorithm is illustrated in Fig. 4. The program first initializes or reads in various parameters that affect the simulator operation. Station-related parameters are first initialized, namely: (1) a distance matrix specifying travel distances between stations; (2) network friction factors that characterize the "impedance" of travel between stations due to items such as traffic signal, stop signs, traffic congestion, etc.; and (3) an initial number of vehicles to be allocated to each station. The initial allocation of vehicles for a specific case of travel demand has been can be optimized using a set of a priori experiments (see Section 3).

```
Initialize:
      read in distance matrix, friction factors;
      allocate vehicles to stations;
      initialize vehicle parameters;
      initialize relocation parameters;

Generate trips;         (based on O/D matrix)

For time = t_start to t_end {
      process events;
      update global parameter database;
      execute relocation process as necessary;
      }

customer arrive event {
      calculate trip time;    (to destination station)
      calculate energy to be used;
      if (vehicle available) {
            assign vehicle;
            execute vehicle departure process;
            }
      else queue customer;
      }

vehicle arrival event {
      process vehicle;
      reduce vehicle SOC;
      }

relocation arrival event {
      process vehicle(s)
      (reduce vehicle SOC)
      }
```

Fig. 4. General simulation algorithm flow in pseudo-code.

Next, simulation events are generated in a time sequence, which are then processed in a time-stepped loop. During each event step, the battery state-of-charge (SOC) of each vehicle is updated according to the vehicle's activity. If the vehicle is in transit, its SOC decreases according to a battery depletion algorithm. If a vehicle is idle at a station, it is charging according to a battery recharge algorithm.

Specific events are also handled in the time-stepped loop, namely a *customer arrive event*, a *vehicle arrival event*, and a *relocation arrive event*. These events (along with specific operating functions) are described below.

Trip time calculations. When a *customer arrive* event occurs at a station, the *station manager* process evaluates the condition of vehicles at the station and assigns a vehicle to be used. If the (predicted) number of active vehicles falls below a minimum threshold, a relocation event is generated, described below. If there are insufficient vehicles to handle the demand, customers are queued at the station. There is a built in "give-up" variable for each customer which dictates the length of time a customer remains in the queue before leaving due to impatience. Immediately after *vehicle departure*, a *vehicle arrive* event is scheduled at another station based on calculating the trip time. The trip time calculation depends on several variables, such as the boarding time, the transit time, the unload time, and the time required to prepare the vehicle for another trip. The transit time is the dominant factor and is calculated as follows: The distance between the origin and destination station is known a priori, along with the amount of "impedance" caused by traffic signals, stop signs, congestion, etc. This impedance is represented by a friction factor for each particular trip. Thus, the transit time is calculated based on taking the trip distance, dividing by the maximum cruise speed of the vehicle, and then divided again by the friction factor:

$$transit\_time = \frac{distance}{max\_cruise\_speed} \times \frac{1}{friction\_factor}.$$

In the simulation, the total trip time is calculated as:

$$total\_trip\_time = boarding\_time + transit\_time + unload\_time.$$

A critical measure of performance is the amount of time a customer has to wait prior to using a vehicle. If a vehicle is available, the wait time is set to a minimum value, which corresponds to the time it takes to get the customer and vehicle together. However, if there are no vehicles available at the station, then the customer is queued until one arrives at the station, either through a standard vehicle arrival or through a relocation event. This can add significantly to the overall wait time. As mentioned, a "give-up" mechanism exists where customers occasionally drop from the queue.

2.3.4. Relocation mechanism

If the amount of demand exceeds the supply of vehicles at a station, the number of available vehicles will quickly be depleted. In order to avoid long customer delays waiting for a vehicle to show up from someone else's trip, there is a relocation mechanism which transports vehicles from a station with an excess of vehicles to the station in short supply. In the real world, the relocation of vehicles can occur either using a large truck that can carry or tow several shared vehicles, or by having the vehicles platoon under their own power. The number of vehicles in a relocation is variable and is treated as an input parameter. A travel time is also associated with a relocation event, again based on the distance and friction factor between stations. This is used in calculating the customer's wait time when there are no vehicles immediately available.

Several algorithms have been developed that determine when and how a relocation occurs:

- *Static relocation*. Based on immediate needs at a particular station, vehicles can be relocated from another station. A minimum threshold can be used before a relocation event is generated for a particular station. Also, the station with an excess of vehicles can also maintain a minimum threshold before it can give-up vehicles in a relocation event. Although simple to implement, this type of relocation mechanism is not very efficient when compared to other *predictive* methods.
- *Historical predictive relocation*. This type of relocation mechanism uses knowledge of expected vehicle demand in the future in order to determine when and from where a relocation event occurs. After a shared vehicle system is in place for a while, it is possible to determine trends in travel demand that can be used to an advantage when scheduling relocations. For example, if at lunch time a large demand is required to go from one station to another station that has many restaurants nearby, relocation events can occur prior to the lunchtime demand in order to minimize customer wait time. The predictive relocation mechanism looks approximately 20 min into the future to determine expected demand.
- *Exact predictive relocation*. If perfect knowledge of future travel demand is available, then relocation events can be optimally scheduled to minimize overall customer wait time. However, exact knowledge is impossible to achieve in the real world, so the best that can be done is to use historical travel demand. In order to generate expected demand, the stochastic trip generation program was run thousands of times, each time with the random number seed slightly different. Each of these runs represents a previous "day" that had similar travel demand. All of these travel demand patterns were then averaged, and the average information is used as the a priori knowledge in the predictive relocation mechanism.

Comparisons have been made between the different types of relocation algorithms, illustrated in the next section.

3. Model results

Using the simulation model, it is possible to track the second-by-second activity of each user of the system, as well as the second-by-second activity of each vehicle. These data can be analyzed in detail to determine the overall system response. Several Measures of Effectiveness (MOEs) have been defined to provide insight to the operational characteristics of the system. Using these MOEs, the system can be iteratively designed and evaluated in simulation, determining preferred operating conditions and critical operational issues. These MOEs are defined below.

3.1. Measures of effectiveness

3.1.1. Average wait time

This MOE corresponds to the average length of time customers have to wait for a vehicle when a vehicle is not immediately available. (The underlying assumption is that users of the system will indeed wait a short time in order to obtain a vehicle.) This MOE is computed by averaging the wait times of all users that had to wait for a vehicle (i.e., the users that did not have to wait for a vehicle are not included in the average; also note that wait time spent by individuals who give up and drop out of the queue is also included).

3.1.2. Total average wait time

The total average wait time is similar to that defined above, but the average is calculated for *all* of the users trips regardless if the user had to wait for a vehicle or not (again, including those that give up and drop out of the queue).

3.1.3. Number of customers waiting

The total number of customers waiting is important to evaluate in conjunction with the wait times. This MOE represents the total number of user trips that had to wait for a vehicle prior to departing from a station.

3.1.4. Number of relocations

During the simulation, vehicles are often relocated from one station to another in order to better meet total system demand. This MOE corresponds to the number of vehicles that are relocated between stations throughout the day. Vehicles that are transferred between stations by users are not counted as a relocation. Each vehicle that is relocated is counted as a single relocation although several vehicles may be relocated in a group.

3.1.5. Average battery state of charge (SOC)

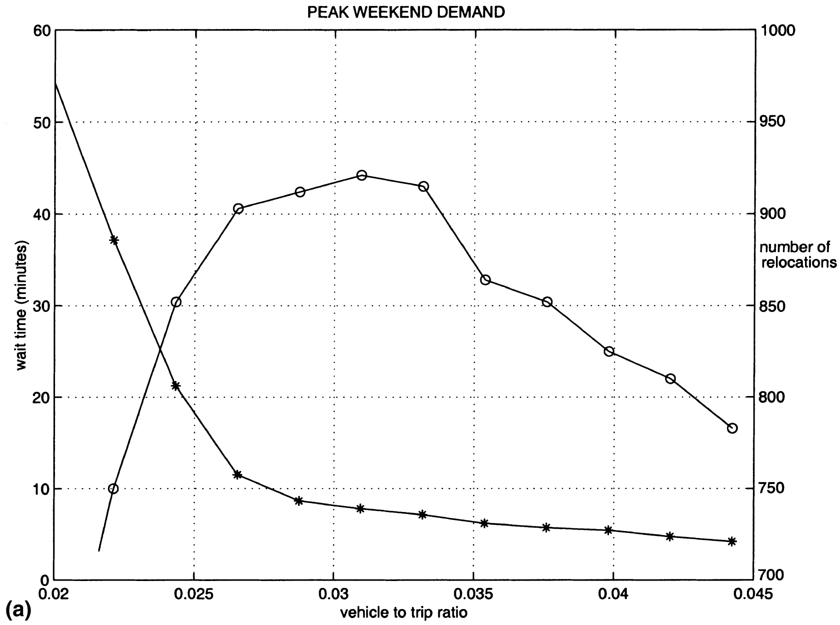
Since electric vehicles have limited range, energy management within the system is very important and is monitored through each vehicles' SOC status. The average SOC of all vehicles is utilized to evaluate the system's overall energy management effectiveness.

3.2. Wait-time and relocation analysis

Two primary parameters are considered when analyzing the system. The first focuses on *vehicle availability*, characterized by a total average customer wait time. The other important parameter is the number of relocation events. For an ideal system, both of these parameters should be kept to a minimum.

Both total-average-wait-time and number-of-relocations are primarily a function of vehicle-to-trip ratio. If there are X vehicles in the system, and Y trips per day, then the vehicle-to-trip ratio is simply X/Y. The vehicle-to-trip ratio is one of the key independent variables, and the results from the MOEs will indicate how many vehicles are needed in the system.

Fig. 5 shows the average-wait-time and number-of-relocations for the six different travel demand levels defined in Section 2.2.2. These results were achieved using the historical predictive relocation technique described in Section 2.3.4. The total number of vehicles in the system was varied from a small amount (approximately 20) to a large amount (greater than 500). Fig. 5a corresponds to the peak weekend demand, Fig. 5b to the peak weekday, Fig. 5c to the mid-peak weekend, Fig. 5d to the mid-peak weekday, Fig. 5e to the off-peak weekend, and Fig. 5f to the off-peak weekday demand. In these graphs, the total-average-wait-time (indicated by stars) consists of not only of the customer queuing time, but also the time required to register, board, and deboard the vehicle (stochastically implemented around a 3 min mean).



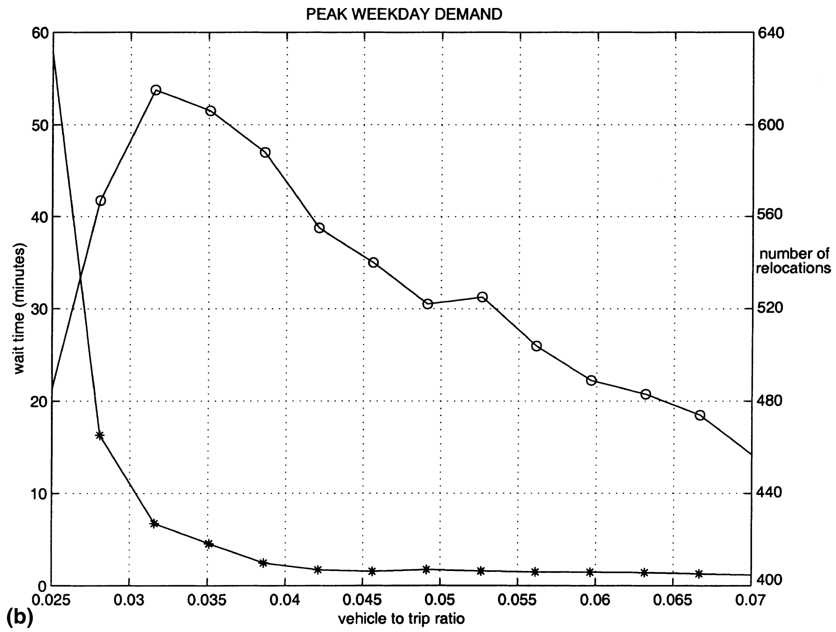


Fig. 5. (a) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for peak weekend travel demand. (b) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for peak weekday travel demand. (c) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for mid-peak weekend travel demand. (d) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for mid-peak weekday travel demand. (e) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for off-peak weekend travel demand. (f) Average customer-wait-time (stars, scale on left) and number-of-relocations (circles, scale on right) as a function of vehicle-to-trip ratio for off-peak weekday travel demand.

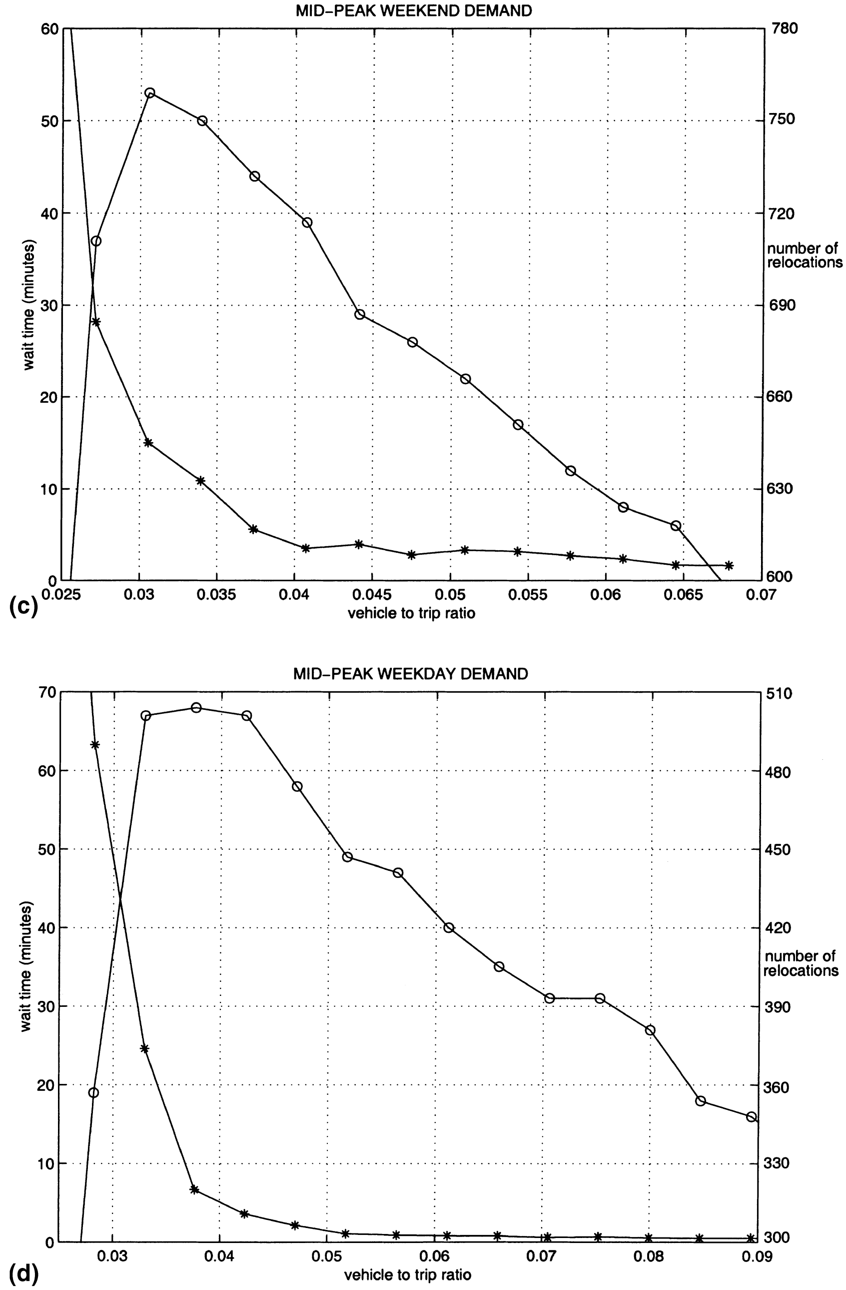


Fig. 5. (continued)

It can be seen in each of these figures that there is a strong inflection in the average-wait-time graphs. For the maximum peak weekend demand, this occurs around 0.03 vehicle-to-trip ratio. The wait time plateaus to the right of this inflection, averaging around 5 min. For the other demand cases, the wait time average of the plateaus is smaller, typically less than 3 min. For the

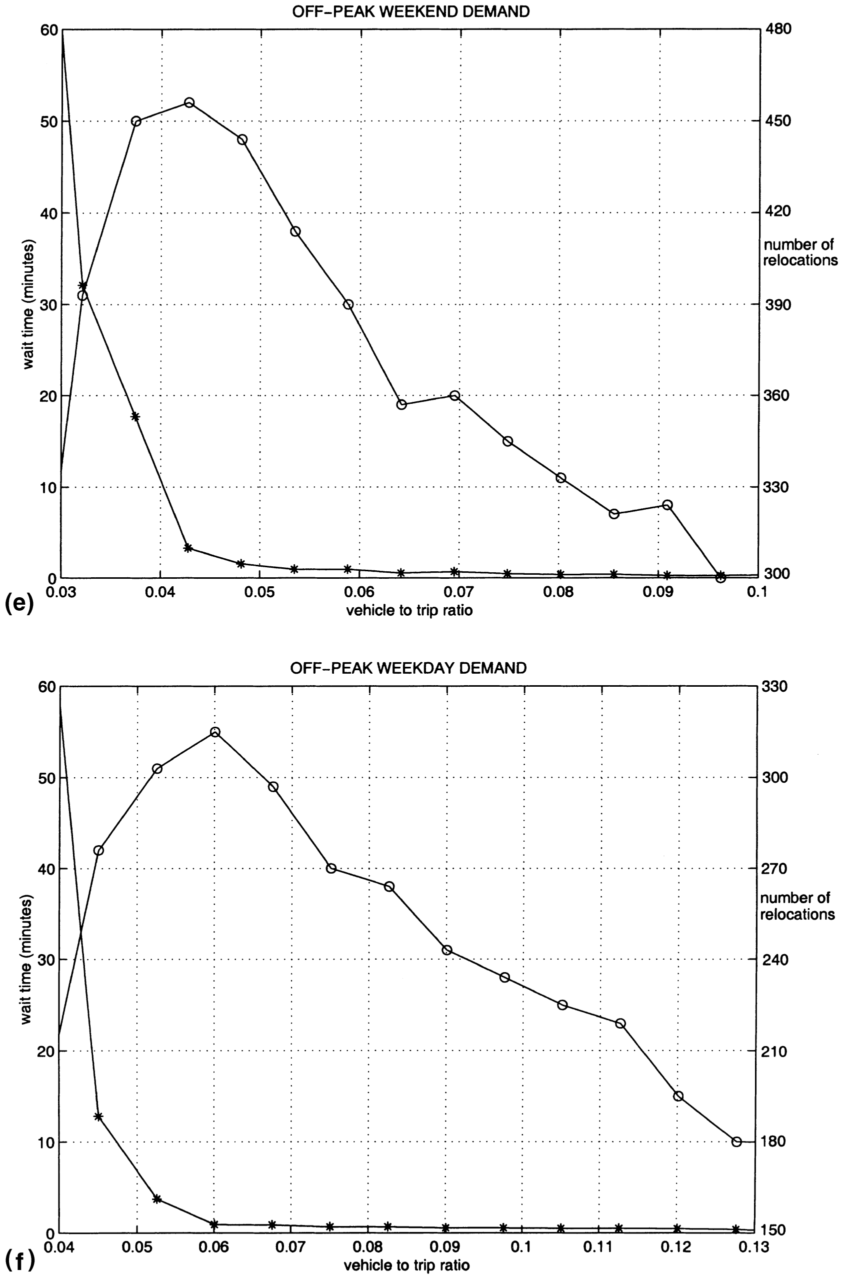


Fig. 5. (continued)

number-of-relocation curves (indicated by circles, scale on the right), there is a peak which typically corresponds to the point of inflection in the wait-time curves. The abrupt increase in wait time to the left of the inflection point represents the lack of vehicles available for relocation. For the maximum peak weekend demand, the maximum number-of-relocations occurs at a

Table 2
Wait time inflection point (a), maximum number of relocation (b) and minimum number of relocation (c) vehicle-to-trip ratios for different travel demand levels

	Peak (Jan–May)	Mid-peak (Nov–Dec)	Off-peak (Jun–Oct)
Wait time inflection point			
Weekend (Fri–Sun)	0.030	0.031	0.042
Weekday (Mon–Thurs)	0.032	0.037	0.058
Max number of relocates			
Weekend (Fri–Sun)	0.030	0.032	0.041
Weekday (Mon–Thurs)	0.031	0.037	0.059
Min number of relocates			
Weekend (Fri–Sun)	0.18	0.20	0.22
Weekday (Mon–Thurs)	0.18	0.20	0.24

vehicle-to-trip ratio of around 0.03. The number-of-relocations drops slowly as the number of vehicles increase, until no relocations are required, corresponding to a vehicle-to-trip ratio of around 0.18. The number-of-relocations to the left of the maximum decrease simply because there are not enough vehicles to relocate in order to meet demand, thereby resulting in high wait times.

For the different levels of travel demand, the wait-time inflection points, the maximum number-of-relocations, and point-of-no-relocations change based on the scale of total user trips. These parameters are summarized in Table 2.

With these graphs and tables, it is possible to determine the best number of vehicles to place in the system. If one ignores the costs of relocation events (but not the cost of vehicles) and observes solely the wait time performance measures, then the best number of vehicles is chosen near the wait-time inflection point. For all of the travel demand cases, this ranges from 3 vehicles per 100 trips to 6 vehicles per 100 trips. With these values, the average customer wait time is approximately 5 min or less (which include registration, boarding, and deboarding time). However, if one also wants to minimize the number of relocations, then a larger number of vehicles will be necessary. There is no inflection point in the number-of-relocation graphs, however a goal of no-relocations can be achieved with 18–24 vehicles per 100 trips.

3.3. Miscellaneous effects on system response

As described in the previous section, the vehicle-to-trip ratio has the greatest effect on the different MOEs of the shared vehicle system. Other design factors that affect the overall performance of the system are described below.

3.3.1. Relocation mechanism

In Section 2.3.4, different relocation algorithms were described. These algorithms were implemented in the simulation model, whose results were subsequently compared to one another. Fig. 6 shows the results of the static relocation, the historical predictive relocation, and the exact predictive algorithms at various vehicle-to-trip ratios (produced for the mid-peak weekend demand).

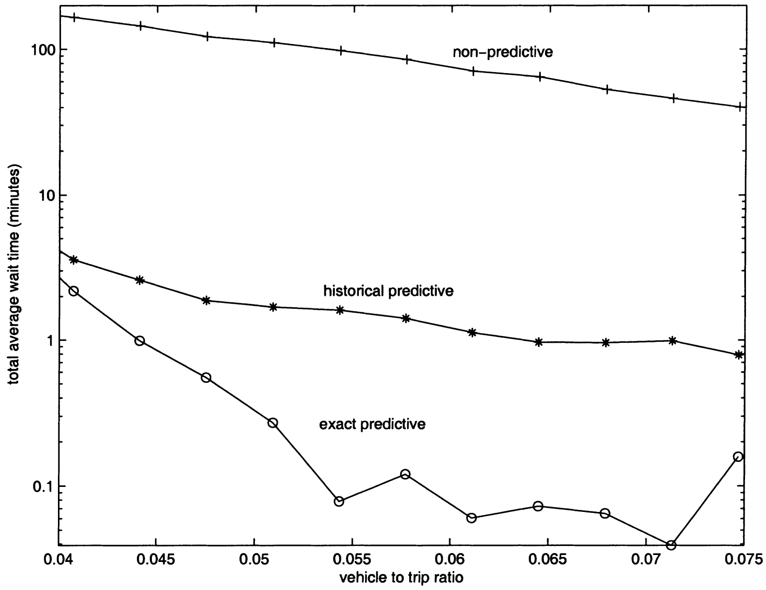


Fig. 6. Log scale of customer total average wait time relative to number of vehicles and relocation scheme. The non-predictive scheme uses no knowledge about demand, exact-predictive uses exact knowledge, and historical-predictive uses a statistical average of demand history.

As can be seen, the exact predictive algorithm has the best wait time results. Remember that this exact predictive algorithm uses "perfect" knowledge of the future, which is unrealistic in a real-world scenario. Much more realistic is the historical predictive technique, which uses accumulated knowledge of travel demand to determine when relocations are necessary. In all cases, this technique performs far better than the static, non-predictive relocation technique.

3.3.2. Station preallocation

The operation of the simulated system is also sensitive to the number of vehicles initially allocated at each station. Similar to the historical predictive relocation technique, it is possible to optimally allocate the vehicles at each station at the beginning of each day, based on minimizing the total number of relocations that occur thereafter. By having the ideal number of vehicles at each station in the morning, both wait time and relocation MOE results were better than having simply a uniform vehicle allocation (e.g., each station gets 10 vehicles).

3.3.3. Number of stations

In the case study, six station locations were chosen based on the historical travel demand obtained (see Section 2.2.2). Additional simulation experiments were also carried out, increasing the number of stations within the entire system. The results of the simulation system scale linearly with overall increased size (increasing both stations and vehicles). If the number of stations is increased while keeping the number of vehicles constant, the number of relocations required increases. In general, the vehicle to station ratio should be at least three to satisfy demand and keep the number of relocations under control.

3.3.4. Vehicle state-of-charge and distances between stations

Electric vehicles are very well suited for shared vehicle systems. They produce very low total emissions and are therefore environmentally beneficial, however they suffer from limited range between recharging. This range limitation is not a problem in a shared vehicle system if the trip distances are small and the vehicles can take advantage of opportunity charging when they are idle at a station. In our shared vehicle system simulation, we model the characteristics of typical electric vehicles available today (e.g., GM EV_1, Honda EVPlus). These electric vehicles have a range of approximately 70 miles driving in urban conditions (based on a 0.3 kWh/mile rating, see e.g., California Air Resource Board, 1995). For the modeled shared vehicle system, the trip distances are less than 5 miles on average. All of the vehicles begin the day with a full SOC. As the vehicles are used and are charged when idle at the stations, the average SOC of all the vehicles never drops below approximately 70% for the highest travel demand case (i.e., peak weekend). As a result, all the vehicles are usable all the time, i.e., none of the vehicles are taken out of service during the day for recharging.

This situation would be different if there was much greater demand, and/or the trip distances were much greater. We were able to modify the simulation to see the effect of SOC limitations on the shared vehicle system. First, it was possible to simulate the case where only a limited subset of stations were capable of charging the vehicles during the day. The system's MOEs were not drastically affected until approximately 50% (3 out of 6) of the stations were charge-station-equipped. In other experiments, the average trip distances were increased. The system was not drastically affected until the trip distances were a factor 3 greater than the distances of the original modeled system.

3.3.5. Vehicle retention

A shared vehicle system such as this is based on "short-term" rental periods (i.e., on a trip-by-trip basis), as opposed to today's typical rental car system where vehicles are rented days at a time. In order to prevent customers from "retaining" a shared vehicle for long periods of time, the vehicle-use cost structure should be set up so that it is very economical to use for short periods of time (say up to 60 min), but is very expensive to use after that. Even with such a pricing mechanism in place, several experiments were carried out with the simulation model to see the effect of long periods of vehicle retention on the overall system. Two input parameters were introduced: (1) the amount of time a particular vehicle is retained; and (2) the frequency upon which customers choose to retain a vehicle for an excessive period. It is possible to vary these parameters, even to the extreme case of a typical rental car system (retention period = 24 h, retention frequency = 100%).

Both parameters of vehicle retention had a significant effect on the system's MOEs. The effects were greater for a system that had a lower number of vehicles in service. Overall, the length of time the vehicles were retained had the greatest influence. For a moderate travel demand case (e.g., mid-peak weekend), it was found that wait times in the system drastically increased when the retention period exceeded 60 min.

3.4. Cost analysis

The shared vehicle simulation model (implemented for a resort community) shows that the average peak weekend demand of approximately 2300 trips/day can be accommodated with approximately 75 vehicles circulating in the system. (Please note that this determination is based on the simulation results, not on any cost analysis.) The economic feasibility of such a system revolves around many parameters which have been evaluated in a cursory cost analysis. The most significant economic issues are the following: set-up/construction costs, vehicle costs, personnel costs, automation, and customer usage rates.

The cost analysis was carried out for four scenarios ranging from labor/personnel intensive to automation/computer intensive. Scenario 1 is very personnel intensive, where the majority of the work is performed manually. Scenario 2 adds a small degree of automation, such as registration kiosks and distributed system control. Scenario 3 eliminates more personnel through the use of additional automation (ITS technology) and centralized system control. Lastly, Scenario 4 uses automation as much as possible, even to the point of implementing autonomous relocations. [The specific details of these scenarios is beyond the scope of this paper, and can be found in Barth and Todd (1997).]

Each scenario was evaluated for economic cost recovery periods of one, three, five, and ten years. Overall, the personnel intensive scenarios were found to be very costly for operating periods greater than one year. Additionally, the highly automated scenarios were found to have extreme set-up costs which required lengthy recovery periods. Fig. 7 illustrates the results of the cost analysis. In this figure, the relationships between set-up costs, personnel costs, vehicle costs (including maintenance and attrition), and total costs are illustrated for the various scenarios. A balance between personnel and automation was found to be necessary to compete with present transportation costs (e.g., rental cars, taxis, etc.) in the modeled area. The average cost per trip for each scenario is annotated on the graph.

Further, a cursory daily cost analysis was performed and is illustrated in Fig. 8. The vehicle-dependent costs have been estimated as a function of the number of vehicles used in the system (setup costs and other flat costs have not been included in this analysis). The cost of adding

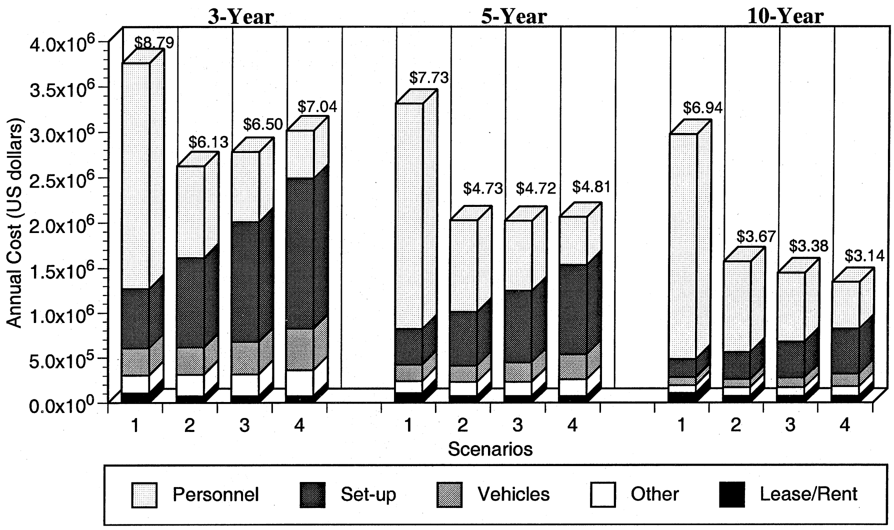


Fig. 7. Scenario annual cost with respect to number of years to recover costs. Each stacked column represents total annual system costs. Average relative trip costs included on top of each stacked column (US dollars/trip).

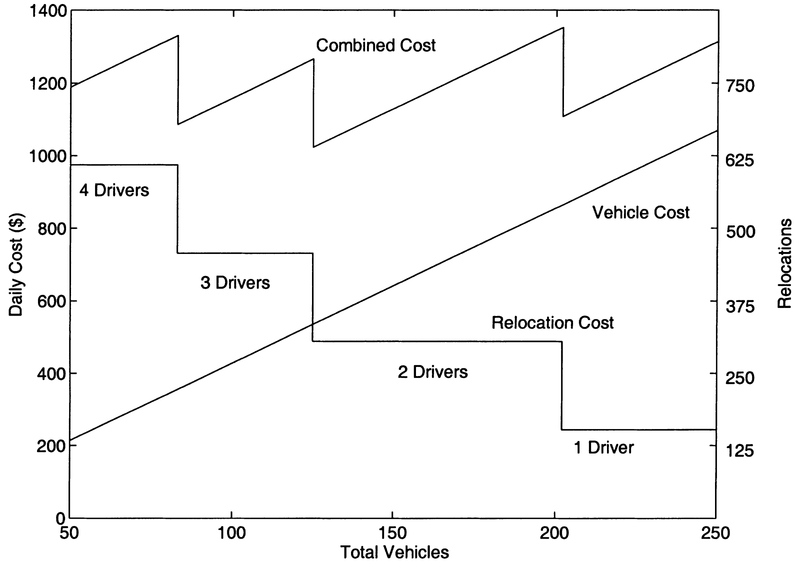


Fig. 8. Vehicle-dependent costs as a function of number of vehicles used in the shared vehicle system (setup costs and other flat costs are not depicted). The shared vehicle costs increases linearly with each vehicle added. The relocation costs decrease stepwise as a function of truck/driver combinations.

vehicles to the system increases linearly with each vehicle. These costs include not only the initial purchase cost of the vehicle, but also costs for maintenance, energy, etc. (The linear increase in vehicle costs is a rather simplistic assumption and does not take into account any economy-of-scale.) Also shown is the cost for implementing the designed relocation mechanism based on estimating the personnel and equipment required for the relocation demand. This cost takes on a "staircase" shape due to the incremental costs for each additional driver and truck required for relocating (one driver/truck combination can relocate approximately 150 vehicles per day). When these two costs are combined, it is evident that the lowest costs occur at each incremental step in drivers and that the daily cost at these points are approximately the same, independent of the number of vehicles.

4. Conclusions and future work

A powerful simulation model has been developed for evaluating shared vehicle systems, with a particular emphasis on systems that have multiple stations that induce numerous one-way trips. Initially, the model has been applied to a resort community in Southern California. A good deal of effort went into designing such a system for this area, including characterizing travel demand for different seasons. The simulation model has a number of input parameters that allow for the evaluation of numerous scenarios. Several measures of effectiveness have been determined and are calculated to characterize the overall system performance. Using this model, a great deal of focus was placed on average customer wait time and the number of relocations required to keep the wait time low. For six different travel demand cases, it was found that the general shape of the wait-time and relocation curves were similar. For the resort community implementation, it was found that the most effective number of vehicles (in terms of wait time) is in the range of 3 to 6 vehicles per 100 trips in a 24 h day. On the other hand, if the number of relocations also are to be minimized, there should be approximately 18 to 24 vehicles per 100 trips. Various inputs to the model were varied to see the overall system response. The model shows that the shared vehicle system is most sensitive to the vehicle-to-trip ratio, the relocation algorithm used, and the charging scheme employed. A preliminary cost analysis was also performed, showing that such a system can be very competitive with present transportation systems (e.g., rental cars, taxis, etc.).

Although this model was initially applied to a resort community, it is easily adaptable and can be applied to numerous other shared vehicle systems, including both multiple station shared vehicle systems and round-trip shared vehicle systems.

In order to verify many of the simulation results, a prototype system is currently being implemented on the University of California, Riverside campus. A small set of stations will be identified and a fleet of electric vehicles will be used to shuttle faculty and staff to the different stations. This prototype system is scheduled to be in place in early 1999.

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