Auction-based highway reservation system an agent-based simulation study

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ABSTRACT

Based on previous studies of a highway reservation system, this paper proposed an auction-based implementation, in which the users can bid for the right to use a route during a certain period of time. This paper models the auction system with MATSim using an agent-based simulation technique. The agents adopt their own bidding logic in the auction, and the price converges after around 130 iterations, when the number of users using the reserved highway and the total collected revenue become stable. When the overall demand changes, the collected revenue ranges from 5 to 11 dollars per user, and from 0.7 to 1.5 dollars per mile. The auction system can transfer more consumer surplus to the toll road operators, since it is a personalized tolling mechanism. The users are using the reservation system as insurance of a guaranteed congestion-free travel. The auction-based highway reservation shows great potential as a new traffic management system.

1. Introduction and background

Adding more capacity by providing additional infrastructure has been one of the most fundamental congestion mitigation solutions in most growing urban regions. However, due to budget constraints and lack of available lands, roadway supply almost always increases at a slower rate than the traffic demand growth. In addition, increasing roadway supply may not be able to alleviate peak-hour congestion since reduction in congestion might induce departure time shifts into peak-hour (Hendrickson and Plank, 1984). As a result, researchers have shifted their focus from the supply side to the demand side, with demand management strategies such as congestion pricing and High-Occupancy-Vehicle/High-Occupancy-Toll lanes (Lou et al., 2011; de Palma and Lindsey, 2011), and parking management (Qian and Rajagopal, 2014). One of the emerging innovative demand management approaches is “highway reservation.” The idea behind this is slicing the highway resource into pieces by time and space and allowing users to reserve them in advance so that oversaturation traffic flow does not appear by limiting the total number of reservations. When the highway slots of a certain time interval have been fully reserved, additional users either switch their departure time or use unreserved routes. Different from airline seats, which have clear boundaries, the highway resource does not have a clear edge. Thus, it can be sliced into time intervals and links separated with on- and off-ramps.

A few studies (Wong, 1997; Gerla and Iftode, undated; Iftode et al., undated; Su and Park, 2014) demonstrated the promising performance of the proposed highway reservation system without explicitly considering realistic queueing behaviors and travel times. For example, our previous study (Su and Park, 2014) minimized the total system cost by allocating the
sliced highway slots to the users. In the two case studies, the optimized system costs were at least 20% lower than corresponding user equilibrium conditions. An important finding is that in the optimized trip schedule, all the link flows are under capacity, even though the model did not have a capacity constraint. This finding justifies a capacity constraint through a reservation system. An optimized trip schedule is a centralized way of allocating the highway resource to users, based on assumptions of homogeneous users and 100% compliance rate. However, this is not the case in real life. That's why we propose a multi-agent-based model to simulate users' heterogeneous behaviors in an auction system.

Here is how it works: A reservation center operates the highway in a metropolitan area. The travellers notify the reservation center their desired route and on-ramp entrance time interval, and put in a bid for it. The reservations are handled in a sequence of the bids from high to low. When a link in the requested route has been fully reserved, that request is rejected, and the user either submits a new request with a higher bid or a different time interval the next day. If all of the links of the requested route are available, the request is accepted and the user is charged the amount of the bid.

In this paper, an auction system is proposed over a First-Come-First-Serve (FCFS) rule in the reservations. FCFS policy works in many reservation-based-scheduling services like doctors' offices and vehicle maintenance, in which users with strong preferences for certain times will typically be the “first-comers” to reserve that time. However, when traffic congestion becomes such a big problem and everyone wants to be “first-comers”, the FCFS rule will not work. For example, all users want to reserve a 7:30 am time, and they all submit the reservation request right after the system opens. If the system is web-based, that probably means the sequence of receiving these requests are based on milliseconds difference, making FCFS an infeasible solution.

What's the advantage of a reservation system over a time-varying toll? The toll on a High-Occupancy-Toll (HOT) system can change by the travel distance and by the overall demand level, but not by users or vehicles. The beauty of an auction system is that price is directly determined by the users through competition, or market. So an advantage of a reservation system is varying the toll by users. A major problem with HOT systems is that users sometimes are not quite sensitive to the price, and increasing the toll may not avoid a break down in a HOT lane. This problem is solved in the reservation system by imposing a capacity constraint.

The contribution of this paper is to explore the feasibility of implementing a highway reservation system using an auction-based approach. Auction theory focuses on single commodity auctions, while the highway slots are in thousands, and they are not independent. For example, if the freeway link between ramp 2 and 3 at 8:30 am are fully reserved, all the other routes that need this link at 8:30 am, including from ramp 1 to 3 or from ramp 2 to 4 become unavailable. An agent-based simulation technique is adopted to study such a complicated auction structure. The remainder of the paper is organized as follows: Section 2 briefly discusses previous studies and highway reservation concepts and other auction-based traffic management, followed a description of the auction-based reservation architecture. Section 4 describes the traffic network structure of a case study and its travel demand using an OD matrix. The “Results” section describes the simulation outputs and findings. Section 9 presents the issues that need to be considered but not modelled in this paper. Finally, Section 10 highlights the findings from the simulation, and future research ideas.

2. Literature review

The concept of road reservation or trip-booking is mentioned in the literature as early as the 1990s (Wong, 1997; Gerla and Iftode, undated; Iftode et al., undated). Wong (1997), Gerla and Iftode (undated), and Iftode et al. (undated) discussed basic functions, advantages and difficulties of a highway booking system. Extensive modelling efforts were not done until the past 5 years. McGinley et al. (2010) showed that a reservation system is necessary to avoid waiting when the mean waiting time is large at the optimal point of operation. Studying the reservation system on a single bottleneck with heterogeneous users, Koolstra (2000) found all queuing costs can be eliminated without increasing the mean rescheduling costs. Another finding is that a freeway reservation might be more effective in practice than road pricing. de Feijter et al. (2004) showed that trip booking can improve reliability and predictability of travel times. Since travel time uncertainty can account for a large proportion of the morning commute cost (Robert and Small, 1995), the improvement of travel time reliability could be a huge benefit of the reservation system. Edara and Teodorovic (2008) conducted extensive modelling work of reservation systems, proposing a Highway Allocation System (HAS) and a Highway Reservation System (HRS). The goal of HAS is maximizing the total Passenger-Miles-Travelled over a period by selecting trips from received booking requests. HRS assumes an incoming booking request flow and makes an on-line decision to accept or reject a request. A potential limitation with HAS is using Passenger-Miles-Travelled as objective, as it is biased toward longer distance trips. HAS did not consider explicitly the departure time adjustment, which is the core role of reservation systems.

Due to the fact that highway does not have separable seats like airplanes, researchers have proposed different methods to discretize the highway resource. The most common one is slicing highway capacity by links and time intervals (Wong, 1997; Gerla and Iftode, undated; Iftode et al., undated; Ravi et al., undated). Liu et al. (2013) used a different approach: a token-based reservation idea from computer science domain. Each road segment has a set of tokens. A vehicle has to be affiliated with a token to travel on that segment. When it arrives at the next road segment, there should be a token on that segment available for this car. Tokens can be reused by multiple vehicles as long as the requested time slots on the token do not overlap. The total number of tokens is the product of the segment length and optimal traffic density, which is determined by Greenshield's model. Thus, the optimal density is a half of jam density, and optimal speed is a half of free flow speed. A critical challenge with this approach is that the amount of time a car occupies a token is hard to determine, since the travel time depends...
on the traffic volume, which is not known until all of the requests have been processed. The second challenge is how to avoid too many tokens being reserved for a short time range, because that would lead to oversaturated traffic in that time.

Adler et al. and Iwanowski are the first researchers that considered using market-based or negotiation-based approaches for cooperative roadway usage. Adler et al. (2005) and Adler and Blue (2002) proposed a principled negotiation process between agents representing network managers and users equipped with route guidance systems. The goal of the negotiation is an efficient distribution of network capacity over time and space, while maintaining individual user’s preference (route, departure/arrival time) as much as possible. However, according to the case studies in Adler et al. (2005), the percentage of users who took the negotiated path ranged between 10% and 20%; a small proportion of the users reached a common end with the network manager. Iwanowski et al. (2003) discussed the concepts of several market-based approaches for road traffic coordination. In the auction-based traffic control system, all rights to use road segments are distributed by auctions, and the auctions are conducted periodically. All of the biddings are handled by vehicle/user unit, which represents the user’s individual interests and strategies. The vehicle/user unit uses an automated software unit to participate in an electronic trading process, to bid for the right of using certain road segments. The advantage of an auction-based mechanism is the independence of a prior set-up of traffic models and analysis. Our paper has adopted this auction-based mechanism into the reservation system.

Using a redistribution mechanism to realize a money flow among participants has been discussed by researchers to solve the social equity issues related to toll roads. In the auction-based approach discussed by Iwanowski et al. (2003), the collected tolls are credited to all the participants uniformly. However, a more delicate redistribution algorithm should be considered since some participants might sacrifice more and deserve more refund. In the exchange-based trading approach (Iwanowski et al., 2003), participants directly exchange the roadway using rights, like stocks. Adler and Cetin (2001) redistributed the toll collected from a more desirable route to users on a less desirable route, and created a user equilibrium assignment.

Multi-agent based modelling techniques have been used by numerous studies in transportation. Hallé and Chaib-draa (2005) applied it in modelling a collaborative platooning system. Galland et al. (2014) used an agent-based model to assess individuals’ carpooling mobility behavior. Wahle et al. (2002) modelled the impact of real-time information in a two-route scenario using an agent-based simulation, and explored the impact of using different types of information. MATSim is an open-source software that provides a framework to implement large-scale agent-based transportation simulations (MATSim, 2014). It has been applied by numerous researchers in traffic impact analysis, road/congestion pricing analysis, carpooling, freight modelling, environment effect evaluations, and evacuation plans (Charypar and Nagel, 2005; Schroeder et al., 2012; Neumann and Nagel, 2013; Onelcici et al., 2013; Comi et al., 2014; Manley et al., 2014). Agent-based simulation is rather effective when a process includes numerous heterogeneous participants interacting with each other in a decentralized way. The auction-based reservation system is exactly such a system.

3. Description of the agent-based simulation of the highway reservation auction model

A Reservation Management Center (RMC) is responsible for making full use of the highway system, i.e. maximizing the throughput, efficiency, and reducing safety issues. User agents represent individual user’s interest and preference. The user agents notify the RMC their preferred route and on-ramp time interval with a bid. Then, all the conflicting requests (i.e., with routes that share the same links at the same time) are sorted by the bid from high to low, and handled by the RMC in sequence. Only if all the requested links are available, that request will be accepted, and the agent will be charged the bid amount, then the RMC will move on to the next request. For a user agent that submits multiple requests, one request being approved will automatically remove the rest of them from the queue. The RMC maintains a spatial–temporal table to manage the reserved highway resource: when a new request is accepted, the corresponding cells in the table are updated (i.e. plus one). Thus when part of the requested links are not available, that request will be rejected. The user agents’ requested time is based on the on-ramp time interval, and the users are responsible for arriving at the on-ramp by the requested time.

The maximum link flow is set to be 1800 vehicles/h/ln, with a 60 mph design speed. Since the time interval used in this research is 2 min, a maximum of 60 vehicles \( \frac{1800 \times 2}{60} = 60 \) are allowed into a link within one time interval. Note that the maximum link flow is not fixed and might change in different situations, which will be discussed at the end of the paper. For each reservation request (a route/time combination), the RMC needs to estimate the arrival time at each of the links, to determine which cells in the spatial–temporal table the RMC should check to see if the capacity constraint has been violated. Under the design speed of 60 mph, the arrival time can be estimated with high accuracy. For this purpose, the reserved lane design speed needs to be maintained, through speed-control and merging-assistance systems. How to maintain the design speed is not the focus of this paper, but existing Cooperative Adaptive Cruise Control and platooning control strategies are helpful (Hallé and Chaib-draa, 2005; Darbha and Rajagopal, 1999; Bifulco et al., 2013). Note that the design speed changes by road geometry, pavement quality, weather, etc.

The testbed in this paper models a 13-mile long freeway with a parallel arterial during the morning peak hour. The commuters can use either the reserved highway or the arterial. Since the arterial has a lower speed limit and is open to all traffic, its travel time is generally much longer than the highway and has larger variability. The user agents follow a simple logic when choosing from the two: use the highway only if the total cost of using the reservation system is lower than the cost of using the arterial. The highway cost includes cost of travel time, cost of early arrival at work, and bid cost. Note that it does not include the late arrival cost, since we assume users would not bid for the time intervals that make them late. User agents are heterogeneous in terms of value of time. The cost of early arrival time is zero if a user arrives right on time. The total arte-
rial cost includes cost of travel time, cost of early or late arrival, and cost of travel time variability. The arterial travel time variability is modelled by adding twice the standard deviation of travel time to the mean travel time (Schrank et al., 2012).

The user agents’ logic is a blind search: it starts from the most desired time interval, which is calculated as the departure time to arrive at work right on time. If the agent cannot win even if paying his/her maximum bidding amount (i.e., the amount that makes highway and arterial cost equal), it will move to an earlier interval. When it moves to a time interval so early that the highway cost with zero bid is equal to the arterial cost, the agent will simply use the arterial from now on (with a 5% chance of coming back to reservation system in our simulations). A variable with five enumerates is used to flag an agent’s state. In the first iteration, the agents bid for the most desirable time interval with a randomly-generated bid. At this time, this agent’s state is “INITIAL” (Blocks 3 and 4 in Appendix A). If succeeded, the agent will try to lower the bid in the next iteration, since it might be overpaying for it. This agent is in “DECREASING” state (Blocks 5 and 6 in Appendix A). The “DECREASING” state continues until the agent fails, then the last successful bid would be taken as the optimal strategy. Now the agent enters “STABLE” state (Block 8 in Appendix A), and will keep on using the optimal strategy. If the agent lost the initial bid, it will try to increase the bid (“INCREASING” state) (Blocks 4 and 7 in Appendix A) till success (“STABLE” state), and adopt the successful bid as optimal strategy. The optimal strategy might still lose, since other agents might move to the time interval with a higher bid. In that case, the agent will start an “INCREASING” state again. Also the “STABLE” agents will keep an eye on the arterial travel time and will reduce the bid accordingly when they find the arterial cost reduces.

In the “DECREASING” and “INCREASING” states, the agents change the bid by a step size, named Delta. In the “DECREASING” state, when the bid has been reduced to just below Delta and it still wins, the agent will stop the “DECREASING” state, and use the last bid, which is slightly lower than Delta but not zero, as the optimal strategy. This is Delta’s other function: a threshold for “zero”, i.e. bid is treated as zero when it drops below Delta. In the “INCREASING” state, if increasing the bid by Delta makes the total reservation cost higher than the arterial cost, the agent will move to an earlier interval and set the state as “INITIAL”. If an agent keeps on moving to earlier intervals and suddenly finds that the value of time cost of using reservation system (excluding bid cost) is higher than the arterial cost, it means arterial is the optimal strategy for this agent, and it will set the state as “ALT” (Block 9 in Appendix A). This is a blind and greedy search, since the user agent tries different intervals step by step, and stops when it finds a satisfactory strategy, instead of going over multiple intervals and selecting the lowest-cost one. This assumption is reasonable, when the other users’ bidding information is not disclosed.

Regarding a bid changing step size, the simulation takes too long to converge if Delta is too small. If Delta is too big, it might lead to unnecessary oscillations of the users’ states, which are observed in early stages of the simulations. Delta should change with each agent since agents have different values of time. We tried different settings of Delta and finally found that the simulation worked well when Delta is set to 7% of the average arterial cost.

In the “ALT” state, the user agent will stick to the arterial, but with a 5% chance of giving the reservation system another try. The rest (95%) of the “ALT” agents and all the agents rejected by the reservation system will have to use the arterial. The arterial departure time choice is critical to the simulation, and the logic (Block 10 in Appendix A) used in this paper is as below. The user agents will use the historical arterial average travel time and average arrival time of agents between the same OD pair. If the average arrival interval of the last iteration is less than 5 intervals earlier or less than 2 intervals later than the desired arrival time, the agent will simply use the average departure time in this iteration, plus or minus some randomness. Otherwise, the departure time in this iteration will be adjusted earlier or later based on the deviations of the average arrival time from the desired arrival time. If there is no historical data of that OD pair, the overall average arterial speed will be used. The agent calculates the average travel time based on the average arterial speed and subtracts travel time from the desired arrival time to get the departure time for this iteration. Note that all the actual departure time has some randomness added (±2.5 intervals) before being fed to MATSim, to avoid some intervals being oversaturated.

The agents are heterogeneous in terms of time values. The value of travel time is assumed to follow a lognormal distribution with mean value $15.56/h and standard deviation $4.78/h, according to a report (Parsons Brinckerhoff et al., 2013). The values of early and late arrival time at workplace are also lognormal, with $9.44 (2.9)/h and $38.28 (7.54)/h (standard deviations in the parenthesis). The value of early and late arrival is derived from the value of travel time based on the ratios from Small’s study (Small, 1982). We imposed a constraint to the time values: the travel time value is at least 30% higher than the early arrival time value, and the late arrival time value is at least 30% higher than the travel time value. If these two criteria are not satisfied, a user’s value of time will be redrawn from the lognormal distributions.

### 4. Case study testbed

We idealized Interstate 66 (I-66) and its parallel US-29 in Virginia between Centreville and Interstate 495 (I-495) as the simulation testbed (Figs. 1 and 2). This is a major commuting corridor for users that work in the Washington DC/Arlington/Tysons Corner area and live in the Fairfax/Centreville/Chantilly area. I-66 can be split into 6 links along this route using on- and off-ramps. US-29 is a parallel arterial along I-66. Fig. 1 shows the map of the network with all the nodes, links and connectors. Fig. 2 is an abstract view just showing the zones. I-66 (green links in Fig. 2) is managed by the reservation system, and US-29 (red links in Fig. 2) is open to all traffic. All of the highway and arterial links in the abstract network are two miles long. The maximum allowed flow on the highway is 7200 vehicles/h (four lanes), and 2000 vehicles/h on the arterial. The

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1 For interpretation of color in Fig. 2, the reader is referred to the web version of this article.
The design speed of the highway is 60 mph. The speed of the arterial is set to be 20 mph, which is relatively low since the traffic signals are not modelled in the testbed. The time interval is 2 min.

A total of 23,000 users are assumed to travel on this network on a daily basis. The OD matrix is shown in Table 1. Trips that need a single highway link are not considered, since they are too short and users are more likely to use local roads. The desired arrival times of all of the 23,000 users or agents are randomly assigned: 10% 8:00 am, 20% 8:30 am, 50% 9:00 am, and 20% 9:30 am. Once generated, a traveller table is used for all the simulations including the MATSim DTA.

We developed a program to feed MATSim with individual travellers’ departure time, have MATSim do the network loading, and analyze MATSim output to obtain arrival times of individual travellers, as input to agents in the auction simulation. To be more specific for readers that are familiar with MATSim, we did not use MATSim’s replanning module, instead we used the auction system to generate the trip plans and feed them to MATSim’s network-loading module.

5. Results

5.1. Converging process

Fig. 3 shows the converging process. Only the highway users’ curve is shown while the arterial users’ curve is not, since the total is always 23,000 trips. At the beginning of the simulation, all of the users try to reserve their most desired time interval, and these intervals cannot take them all, due to the capacity constraint. So only a small number of users with the highest bids win, and the others are rejected. This explains why the number of highway users is fairly low at the beginning as shown in Fig. 3. Since a lot of users are rejected and have to use the arterial, the arterial is severely congested, generating extremely high arterial travel cost. Thus these user agents bid very high. That’s why we see the total collected revenue increases quickly at the beginning of the simulation, as shown in Fig. 3. As time goes on, users begin to bid earlier
time intervals and win, thus fewer and fewer users use the arterial, relieving the arterial congestion, and lowering the bids. So the total revenue decreases. When the number of users actually accepted into the reserved highway and the total collected revenue becomes stable at around the 130th iteration, the simulation converges, as shown in Fig. 3. The converging revenue is 154K dollars, and the converged number of highway users is 19,170. Fig. 4 illustrates that for the users with the same OD and same desired arrival time (DAT), those winning later intervals have higher value of travel time in general.

Fig. 5 shows how the number of users in the states “ALT”, “INITIAL” and “STABLE” change by iteration. After 150 iterations, the number of users in these three states becomes fairly stable with minor fluctuations. The fluctuation comes from the arterial travel time variability, since “STABLE” users keep an eye on the arterial travel time and will reduce the bid and change the state to “INITIAL” if they find themselves overpaying. Whenever arterial travel time drops, more agents become “STABLE” and “INITIAL” users drop. At convergence, the number of highway users (Fig. 3) is much more stable than the number of users in the three states in Fig. 5, since the reserved highway users could come from any of the “INITIAL”, “STABLE”, “DECREASING” and “INCREASING” states.

5.2. Bidding cost analysis

The total collected revenue at the convergence is $154,000 per day, $8.00 per user, or $1.07 per mile. Since the users decide how much to bid based on comparing with arterial cost, they pay more when the total demand level becomes higher. Table 2 shows the sensitivity analysis of changing the demand level from 17K to 29K (by shrinking or expanding the OD matrix in Table 1). As the demand grows, the bid cost per user and the average collected revenue per mile increases. Note that other than this sensitivity analysis, all of the discussions in this paper are based on overall demand level 23K.

The bidding amount depends on how much cost a user agent can save by switching from the arterial to the reserved highway. As the trip length becomes longer and the arterial more congested, the agents bid higher. But it also depends on the demand level over a period. Given a traffic network, OD matrix, travellers’ value of time, and their desired arrival time, the agent-based simulation tool tells how much are users bidding for certain routes and time intervals. Fig. 6 shows the bids of three OD pairs: (1,4), (1,7) and (3,6). Below are the four findings from these plots.

(1) The bid increases by time for users with the same DAT. In the simulation setting, the agents want to arrive at the workplace right on time instead of being early or being late. Thus, early time intervals closer to the DAT are more attractive. That’s why users generally pay higher for these.

(2) For the agents from the same OD pair, their bids for a particular interval are close, no matter what DAT they have. This is easy to understand, since the RMC does not know these users’ DAT. All it does is sort the requests by bid and handle
Due to the existence of the “decreasing” process in the agents’ decision-making, they all end up paying very similar prices.

On the other hand, longer-trip users bid higher, since they save more time by switching from the arterial to the reserved highway. From this perspective, the longer trips are favoured by the reservation system. However, the longer trips pay almost the same for the same interval, although OD (1,7) trips are 12 miles long while OD (3,6) trips are 6 miles long. Comparing OD (3,6) and OD (1,4), they have the same distance, but OD (3,6) agents pay much higher than OD (1,4), because OD (3,6) includes more bottleneck links.

Agents with DAT 9:30 am are much lower than bids from other agents. That’s because 50% of the agents have DAT 9:00 am, and these agents use time intervals as early as 7:20 am: pushing up the price of all of the time intervals earlier than 9:00 am. As a result, agents with DAT 8:30 am and 8:00 am have to bid as high to win. However, the agents with DAT 9:30 am are not in the “pre-9:00” market, as they can use intervals between 9:00 am and 9:30 am. When the majority want to arrive at work before 9:00 am, being able to go half an hour later can save a lot of travel time, or money in this case.

To see how much benefit the auction-based reservation system can bring to this highway/arterial network, we compared the total travel time of the reservation system with MATSim’s dynamic traffic assignment (DTA) module. The MATSim module works in a different manner with the reservation system, as explained below.

MATSim uses all-day activity plans as search space to maximize a fitness function, as shown in Eq. (1) (Charypar and Nagel, 2005). Using all-day plans means the activity durations can be shortened or extended and it will affect the fitness function. However, the highway reservation system in this research is based on the morning commuting trips from home to work, without modelling the activity durations. The home-to-work trips are translated to MATSim daily plans by assuming the day ends with the work activity. We used the same desired arrival time with the reservation system of all of the agents’ work activities. To make apple-to-apple comparisons, or have MATSim mimic the reservation system users’ behavior, we manipulated the “activityTypicalDuration”, “activityOpeningTime” and “activityLatestStartTime.” For example, if an agent’s desired arrival time is 8:00 am, we set the “activityTypicalDuration” of home activity as 8 h (as it starts from 12 am), the “activityOpeningTime” of work activity as 8:00 am, and the “activityLatestStartTime” of work activity as 8:00 am. We expect the late arrival penalty be applied if this agent arrives later than 8:00 am. The “activityMinimumDuration” of home activity is set as 6 h to give the agent some room to start early. In the “planCalcScore” section, the “lateArrival” parameter is set to be “–18”, “traveling” is “–6”, “performing” is “6”, and “earlyDeparture” is set to be “0”. Under these settings, however, the resulting departure time of the agents did not spread out. Then, we noticed that “MutationRange” determines the range of the departure time adjustment. It is the parameter that has the greatest impact on the DTA result. So we changed the MutationRange from 600 s to 3600 s and put the corresponding simulation results in Table 3. As shown, in most cases the VHT of MATSim DTA is much higher than the reservation system. When the Mutat-
tionRange is 3600 s, the VHT of the MATSim DTA module is lower than the reservation system, but with some agents’ arrival time as late as 12:30 pm, which is unacceptable and unrealistic. When the actual arrival time is not too late (10:40 am when the MutationRange is 600 s), the VHT is almost twice as much as the reservation system. Thus, the reservation system achieves very short VHT with the departure time range only 2 h and 34 min, much better performance than the MATSim DTA module. The MATSim DTA model can be interpreted as modelling departure time choice in the absence of the reservation system; thus, the performance difference in Fig. 7 can be interpreted as the benefit of the auction system.

Fig. 6. Bid cost plots.
MATSim Fitness Function:

\[ F \equiv \sum_{i=1}^{n} U_{act}(\text{type}_i, \text{start}_i, \text{dur}_i) + \sum_{i=2}^{n} U_{\text{traf}}(\text{loc}_{i-1}, \text{loc}_i) \]  

(1)

Fig. 7 shows a comparison of the departure time distribution of the freeway users in the reservation system and MATSim DTA assignments (default MutationRange). It is clearly shown that MATSim DTA model could not generate very early departure time, but can generate very late departure time.

5.4. Other findings

5.4.1. Catfish effect

In each iteration, a small proportion of agents in the state “ALT” give the reservation system a shot. This is a reasonable assumption, and these users play the role of “catfish.” With the “decreasing” process, if there are no new agents coming to bid during a time interval, the existing agents of that interval will come up with a “trust” to put very low bids. Now some arterial agents bid in the reservation system again, and mostly likely they bid close to the highest price they can afford. In this case, the existing agents have to bid high enough to retain the slots, and the “trust” would not last long even if it exists. Like Sardines that keep swimming to avoid being eaten by the catfish, the reservation system users have to bid high enough to avoiding being kicked out by the returning arterial users.
5.4.2. Social equity

When a toll charge or auction based system is considered for the operation of a transportation facility, one cannot ignore its impact on equity. It is generally understood that toll has a bigger economic impact to less wealthy users. However, studies have shown that less wealthy users approved tolls as much as wealth users (Sullivan, 2000), and all groups make use of the HOT lanes as everyone becomes in a hurry (Levinson, 2010). Levinson concluded that HOT lanes provide more benefit to wealthy users than less wealthy users. While it is clear that less wealthy users approves and uses toll facilities, one has to carefully consider impact of tolls before implementing it.

It is noted that auction-based system has some advantages as can address social equity issue with two potential methods. The first is redistributing the collected bid back to the all the participants, evenly or in proportion to the distance (Iwanowski et al., 2003; Adler and Cetin, 2001). In this case, the agents rejected by the system receive some refund to compensate the losing chances of using the reserved highway, so it is with the agents who have to use very early time intervals. Another way is having the agents bid with some “reservation coins,” instead of directly using money. They are allocated a certain amount of “reservation coins” at the beginning, and can trade them at a free market. In this case, some users can make some profit by selling the coins. This paper will not dig too much into the social equity issue, and leaves it to future studies.

6. Further discussions

In the proposed auction system, request-making and handling are supposed to happen long before the actual traveling time. In some cases, users cannot always make trip plans ahead of time, thus the RMC should also be open to on-the-fly reservations. Since by then the succeeding bids would have been known, the on-the-fly requests will be charged a rate higher than the average successful bids over the same route/time choice, or similar ones. The higher rate is to compensate the risk of causing traffic breakdowns on the reserved links, and it depends on the demand and operational needs.

The 1800 vehs/h/ln capacity and 60 mph design speed is not fixed since work zones, inclement weather, and crashes could lead to a drop of the capacity and speed. For work zones the capacity can be relatively easily predicted, thus the capacity can be set before the auction system opens. For inclement weather and crashes whose influences on the freeway are hard to predict, an emergency-response system is needed, for example, to reroute the agents already on the highway, and the upcoming agents. For example, the agent could receive a message saying “You can choose to leave the highway at the next exit and receive a 100% refund. If you stay on the highway, you might be late for as long as 20 min due to the crash and lane closure.” The system can fine-tune the refund amount and delay warning to adjust the number of agents leaving the highway, so that the amount of agents choosing to stay is still under the capacity level.

The field implementation of such a reservation system also faces some challenges. For example a real-time communications channel between the users and the control center is required for the bidding and speed control. A smooth transition between the reserved lanes and general-purpose lanes is another challenge, since the former could be much faster than the latter, thus special assistance is needed to safeguard a lane-change from congested general-purpose lanes to the fast reserved lanes. The highway reservation system is a potential gold-mine for researchers given these implementation challenges.

7. Conclusions and recommendations

This study shows the agent-based simulation of an auction-based highway reservation system. The reserved highway provides a guarantee of congestion-free traffic, helping reduce both the travel time and travel time unreliability. The price is determined by the participants, and it converges. In the bidding process, users with higher values of time are more likely to get their desired departure time interval, while users with lower values of time either use early time intervals or use the arterial. The converged bidding price changes both by time and space. The closer a time interval is to the most desired interval, the higher the price. The more bottleneck links are included in a route, the more expensive that route is. The assumption that some arterial users still give the reservation system another try keeps the bidding price stable, and avoids “low-ball” offers. A summary of these findings is that price is determined by supply and demand. The auction system is more like a personal tolling system that finds the maximum amount an agent is willing to pay. Or it transfers more consumer surplus to the operators, since high-time-value and risk-averse travellers pay higher. Under the given demand level, the converging revenue is around 8 dollars per user, and 1.1 dollars per mile. The highway reservation system helps solve the under-utilization problem of current managed lanes. When demand is low, the reservation lanes are still used instead of being empty, since users pay very low or zero price for their reservations. In contrast, general managed lanes are likely to be under-utilized at low demand.

The simulation provides a solution to a complex problem, and it consumes a lot of computing resources. The simulation time is proportional to the total number of users, the number of routes, and departure time interval options. For a larger scale simulation, there would be more users and routes, while the number of departure time intervals remains the same. For one agent, the number of available routes is limited even for a metropolitan traffic network, since the focus is the highway and its alternative routes. We are cautiously optimistic about the computational requirements of the model due to technology advancements. Like all models with agent behaviors, the simulation tool requires a large amount of detailed and accurate input data, including the agents’ time values and decision-making logic.
There are three directions of future studies for the auction-based simulation. The first one is an emergency-response system, say how to change the agents’ reservation plans or even persuade some of them to cancel the reservation, when some or all the links cannot reach the designed speed or volume. The second one is modelling a High-Occupancy-Toll over the same testbed, and comparing the revenue with the auction system. Another direction is cracking the social equity issues, by redistributing the collected revenue back to all the agents or using tradable reservation coins to bid instead of money.

Acknowledgments

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Appendix A

A.1. Pseudo code of the user agents’ behavior

/* For a user i going from O_i to D_i, s/he needs to know the average cost of going from O_i to D_i through the arterial, so that s/he can decide the highest price s/he is willing to pay for the reservation system. If more than one user travelled from O_i to D_i in the last iteration, use the average departure time and average arrival time of these users to calculate the arterial cost (which includes late or early arrival cost). Note that the average arrival time is the real value plus 2, Arrival time Standard Deviation, to account for the travel time variability of using the arterials. If no users travelled from O_i to D_i through arterial in the last iteration, we use the average speed of all the arterial users to calculate travel time and cost, without considering late and early arrival cost. */

A.2. Data dictionary

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALT</td>
<td>A state variable, meaning user i’s optimal strategy is using the arterial</td>
</tr>
<tr>
<td>altCostTemp</td>
<td>Arterial travel cost of last iteration</td>
</tr>
<tr>
<td>altTravelCost</td>
<td>Moving averaged arterial travel cost</td>
</tr>
<tr>
<td>ArterialDistance(O_i, D_i)</td>
<td>Arterial distance between user i’s OD</td>
</tr>
<tr>
<td>AverageArterialSpeed</td>
<td>Average speed of all the arterial users</td>
</tr>
<tr>
<td>avgArrInt</td>
<td>Average arrival time interval of the users with the same OD of user i and who used arterial in the last iteration</td>
</tr>
<tr>
<td>avgDepInt</td>
<td>Average departure time interval of the users with the same OD of user i and who used arterial in the last iteration</td>
</tr>
<tr>
<td>biddingAmount</td>
<td>Time interval that user i chooses to pay at the current iteration</td>
</tr>
<tr>
<td>biddingInterval</td>
<td>Time interval that user i chooses to bid at the current iteration</td>
</tr>
<tr>
<td>DAT_i</td>
<td>Desired arrival time of user i</td>
</tr>
<tr>
<td>DECREASING</td>
<td>A state variable, meaning user i won the previous bid, and is decreasing the bid to save some money</td>
</tr>
<tr>
<td>delta</td>
<td>The bid’s moving step size</td>
</tr>
<tr>
<td>earlyArrivalVOT_i</td>
<td>Value of early arrival time ($/h)</td>
</tr>
<tr>
<td>i</td>
<td>A user i</td>
</tr>
<tr>
<td>INCREASING</td>
<td>A state variable, meaning user i lost the previous bid, and is increasing the bid for higher possibility of winning</td>
</tr>
<tr>
<td>INITIAL</td>
<td>A state variable, meaning user i is starting to use the reservation system</td>
</tr>
<tr>
<td>lateArrivalVOT_i</td>
<td>Value of late arrival time ($/h)</td>
</tr>
<tr>
<td>MaxBidAmount</td>
<td>Maximum amount user i is willing to pay if he is bidding for the same interval with last iteration</td>
</tr>
<tr>
<td>mostDesiredInterval</td>
<td>Most desired time interval of user i</td>
</tr>
<tr>
<td>previousBid</td>
<td>Bidding amount of user i in the previous iteration</td>
</tr>
<tr>
<td>previousBidTimeCost</td>
<td>Total time value cost of user i’s previous iteration (not including the bidding cost)</td>
</tr>
<tr>
<td>previousInterval</td>
<td>Time interval that user i bided in the previous iteration</td>
</tr>
<tr>
<td>previousResult</td>
<td>Bidding result of user i’s previous iteration: win or lose</td>
</tr>
</tbody>
</table>

(continued on next page)
A.2. (continued)

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>previousState</td>
<td>State of user i in the previous iteration</td>
</tr>
<tr>
<td>STABLE</td>
<td>A state variable, meaning user i has found the optimal strategy, which includes an interval and price</td>
</tr>
<tr>
<td>state</td>
<td>State of user i in the current iteration</td>
</tr>
<tr>
<td>stdArrInt</td>
<td>Standard deviation of the users with the same OD of user i and who used arterial in the last iteration</td>
</tr>
<tr>
<td>travelTimeVOTi</td>
<td>Value of travel time ($./h)</td>
</tr>
</tbody>
</table>

For a user i: //Considering to use the reservation system

### Block 1

//calculate user i’s cost of using alternative route

If (More than one users used the arterial between user i’s OD in the last iteration) //Use these users’ experiences to calculate the arterial cost

```plaintext
{  avgDepInt = average departure time of these users
  avgArrInt = average arrival time of these users
  stdArrInt = Standard deviation of these users’ arrival time
  If (avgArrInt + 2*stdArrInt > DATi)
    altCostTemp = (avgArrInt + 2*stdArrInt - avgDepInt)*travelTimeVOTi +
    (avgArrInt + 2*stdArrInt - DATi)*lateArrivalVOTi
  else
    altCostTemp = (avgArrInt + 2*stdArrInt - avgDepInt)*travelTimeVOTi + (DATi - avgArrival -2*stdArrInt)*earlyArrivalVOTi
}
```

Else  //Otherwise, use the overall arterial average speed

```plaintext
altCostTemp = ArterialDistance(Oi, Di)/AverageArterialSpeed*travelTimeVOTi
```

altTravelCost = 0.5*altTravelCost + 0.5*altCostTemp  //Smooth the altTravelCost with historical data

delta = altTravelCost*0.07  //The reason for selecting 0.07 is explained in the paper

### Block 2

//calculate the maximum acceptable bidding amount of user i

If (user i bid in the previous iteration)  //Retrieve user i’s info of the previous bid

```plaintext
{  Set previousResult as previous bidding result  //TRUE or FALSE
  Set previousInterval as previous bidding interval
  Set previousBidTimeCost as the previous time value cost
  Set previousBid as previous bidding amount
  Set previousState as previous iteration’s state
}
```

Else

```plaintext
Set previousState as ALT
```

MaxBidAmount = altTravelCost – previousBidTimeCost  //This is a key factor, as it determines the highest price user i can accept. Exceeding this price will make using the arterial a better option
Block 3 //if previous bid was successful, try to reduce the bidding amount
If (previousState is INITIAL && previousResult is TRUE)
{
    If previousBid < delta //previousBid is very low
    {
        Consider the previous bid interval and amount as stable, and put them into
        profile for further uses
        Set state as STABLE
    }
    Else //meaning the user still wants to reduce the bid and see if s/he still wins
    {
        Set biddingInterval as previousInterval
        Set biddingAmount as (previousBid-delta)
        Set state as DECREASING
    }
}

Block 4 //increase the bidding amount or change bidding time interval or use alternative route
If (previousState is INITIAL, INCREASING, or STABLE && previousResult is FALSE)
{
    If (previousBid + delta > MaxBidAmount)
    {
        If (MaxBidAmount – earlyArrivalVOT/30 < 0) //Meaning moving to
        an earlier interval is not an option, since in that case the total cost of
        using reservation system will be even higher than using the arterial
        {
            Consider ALT as stable, and save it into profile for future
            uses.
            Set state as ALT
        }
        Else //Meaning there is room to move to an earlier interval
        {
            Set biddingInterval as (previousInterval-1)
            Set biddingAmount as MaxBidAmount-earlyArrivalVOT/30
            Set state as INITIAL
        }
    }
    Else //Meaning there is still room to increase the bid for higher chances of winning
    {
        Set biddingInterval as previousInterval
        Set biddingAmount as (previousBid + delta)
        Set state as INCREASING
    }
}
Block 5 //decrease the bidding amount

If (prevState is DECREASING && previousResult is TRUE) //User i wants to decrease the bid to save money
{
    If (previousBid < delta) // previousBid is already low enough, so consider it as STABLE
    {
        Set state as STABLE
        Consider the previous bid interval and amount as stable, and put them into profile for further uses
    }
    Else //bid can be further reduced
    {
        Set state as DECREASING
        Set biddingInterval as previousInterval
        Set biddingAmount as min(previousBid - delta, MaxBidAmount)
    }
}

Block 6 //user i has found the stable bid

If (prevState is DECREASING && previousResult is FALSE) // Previous bid is too low, the last successful bid is optimal
{
    Set state as STABLE
    Consider the interval and amount of the last successful bid as stable, put them into profile for future uses
}

Block 7 //stop the INCREASING state, set state as STABLE

If (prevState is INCREASING && previousResult is TRUE) //Stop the INCREASING process, consider last bid as optimal
{
    Set state as STABLE
    Consider the previous bid interval and amount as stable, and put them into profile for further uses
}

Block 8 //In STABLE state, still check if alternative route’s cost

If (prevState is STABLE && previousResult is TRUE)
{
    If (previousBid + previousBidTimeCost > altTravelCost) //even if STABLE, still keep an eye on the altTravelCost
    {
        Set state as INITIAL
        Set biddingInterval as the stabilized interval from profile
        Set biddingAmount as max(0, altTravelCost - previousBidTimeCost)
    }
    Else
    {
        Set state as STABLE
        Set biddingInterval as the stabilized interval from profile
        Set biddingamount as the stabilized bid amount from profile
    }
}
For a user j who uses the arterial: //Put the users who choose to use arterial and who lost the bidding into the arterial, and calculate their departure time.

```
Block 9 //In ALT state, have 5% chance of giving reservation system another try
If (prevState is ALT)
{
    If (Random <= alpha) //Under chances of alpha, ALT users give reservation system another try. alpha is set as 5%
    {
        Set state as INITIAL
        Set biddingInterval as the user’s mostDesiredInterval
        Set biddingAmount as (altTravelCost – reserved freeway travel time cost) //The reserved freeway travel time does not change due to the capacity constraint imposed by the reservation system
    }
    Else
    Set state as ALT
}
```

```
Block 10 //Determine departure time of the alternative route users
If (There are users on arterial of user j’s OD in previous iteration)
{
    avgDepInt = average departure time of these users
    avgArrInt = average arrival time of these users
    If (avgArrInt > DAT + 2) //if the average arrival time is over 2 intervals later than the desired arrival interval, make adjustments to the departure time
    {
        depInt = avgDepInt – (avgArrInt-DAT)*0.3 + (Random()–0.5)*5 //with 5 intervals randomness
    }
    Else
    {
        If(avgArrInt < DAT - 5) //if the average arrival is over 5 intervals earlier than the desired arrival interval, make adjustments to the departure time
        {
            depInt = avgDepInt + (DAT-avgArrInt)*0.3+(Random()-0.5)*5 //with 5 intervals randomness
        }
        Else
        {
            depInt = avgDepInt + (Random()-0.5)*5 // with 5 intervals randomness
        }
    }
}
```

References