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AN AGENT-BASED SIMULATION MODEL FOR DISTRIBUTED VEHICLE SHARING OPERATIONS

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ABSTRACT

Vehicle sharing can increase the efficiency of transportation infrastructures and improve environmental sustainability. A distributed operation model is needed to improve a vehicle's intelligence and autonomy. In this research, we develop an agent-based simulation model for a linear transportation system to evaluate three different vehicle sharing operations that include: 1) an independent operation where vehicles are isolate, 2) a centralized operation which assumes a central supervisor agent controls all the vehicles, and 3) a distributed operation where vehicles can communicate with others and make decisions by themselves. Our simulation results demonstrate that: 1) the centralized and distributed models are significantly better than the independent model for large car capacity, 2) centralized model performs significantly better than the distributed model for large car capacity and small communication range, and 3) the distributed model can perform better than the centralized model for large car capacity and communication range.

1 INTRODUCTION

Transportation consumes 32% of the energy among all the consumption units in the U.S. (Pérez-Lombard et al. 2008). Due to its incomparable mobility, flexibility and freedom to travel, private automobiles account for over 83% of the total passenger trips in the U.S. which contributes approximately 17% of household expenses allocated to transportation, 70% of the total petroleum consumption, and 30% of greenhouse gas emissions (Bureau of Transportation Statistics 2014). Private vehicles occupy 25% of urban surfaces (Shoup and Manville 2005) which are usually in the idle mode for 23 hours per day (Litman 2007). Although a public transit system can provide solutions to reduce transportation cost, energy consumption and greenhouse gas emissions, it may not be well accepted due to its low service quality and flexibility, e.g., causing passenger discomfort and difficulty in accessibility (Sinha 2003). As a result, a large national initiative, shared mobility, has been launched recently to help increase the efficiency of transportation infrastructures and improve environmental sustainability (Laporte et al. 2015). In this research, we focus on shared mobility services in which a vehicle can be driven by a person (e.g., in ridesourcing services) or an autopilot (e.g., in future autonomous vehicle sharing systems) to seek for customers when it is not occupied. Traditional vehicle sharing faces one major challenge, nearby vehicle availability (Li et al. 2016), that prevents it from being widely used in the public. If no vehicle is nearby, a person may be stranded, thus having to wait a long time or walk a great distance. In this situation, this person may give up using shared vehicles for this trip and may be further dismayed of using this service for his/her future travels.

Although the practice of vehicle sharing can be dated back to 1940s in Europe and to 1980s in North America (Shaheen and Cohen 2013), quantitative research on the vehicle sharing system modeling is relatively scarce. Early vehicle sharing systems only served a limited number of members and were regarded as niche markets (Millard-Ball et al. 2005). Based on the existing fleet assignment models (Du and Hall 1997), several modeling approaches were adopted to analyze the operations of vehicle sharing systems. Simulation models (Barth and Todd 1999, Ciari et al. 2009, Uesugi et al. 2007) were built to analyze the sensitivity of the system cost and the service quality to system parameters such as fleet size and vehicle relocation. Vehicle sharing has also been investigated in the context of autonomous vehicles (AVs). For example, the autonomous taxi service that has a fixed taxi service and allows AVs to operate between stands and pick up passengers is investigated (Ford 2012) where vehicles can relocate to more favorable locations for potential next demand when needed. While promising, we notice that most of the existing research focuses on centralized operations of vehicle sharing where each vehicle is subject to the same central dispatcher's control. The centralized models impose substantial communications and computational requirements that prohibit their application for large-scale real-world vehicle sharing problems (e.g., possibly involving millions of vehicles running on a massive transportation network in a metropolitan area). Today, with the rapid development of the Internet of Things technologies (Atzori et al. 2010), spatially and temporally distributed vehicles and passengers embedded with mobile devices, software, and sensors can freely form interconnected networks to collect and exchange data, and improve vehicles' localized intelligence to maximize their own interest.

Various models and algorithms have been developed to study the distributed decision problems, such as game theory (Xiao et al. 2005), marketing approach (Jennergren 1973, Sandholm 1998), coalition theory (Klusch and Gerber 2002), collaborative optimization (Tappeta and Renaud 1997), just to name a few. However, most of the existing distributed implementations are not absolutely parallelized or have relatively complex structures (e.g., peer-to-peer structure) which prohibit their applications for large scale vehicle sharing problems. In this paper, we will explore the applications of swarm intelligence for distributed operations of vehicle sharing. In our proposed distributed model, we envision that certain collective behaviors (e.g., cost effectiveness, robustness) can emerge when individual vehicles can form swarms with others in their neighborhood to freely exchange information. Through mimicking the behaviors of ants which emit pheromone to the environment to enable efficient communication with others to search food (Dasgupta 2008), a digital pheromone mechanism is designed to enable efficient indirect communication among vehicles. We will develop an agent-based simulation model to compare the performance of the centralized and distributed models for vehicle sharing operations under various settings of car capacity and communication range. In this exploring study, we explore a linear transportation system since its simple structure can easily reveal managerial insights while it is also commonly seen in practical transportation systems (e.g., a transportation corridor or a strip-shaped city). Four performance metrics including total time steps to deliver all the passengers, average vehicle idle time, average passenger waiting time, and maximum passenger waiting time are proposed to evaluate the vehicle sharing operation models.

This paper is organized as follows: the agent based simulation models for vehicle sharing operation are introduced in Section 2, followed by the simulation results in Section 3, and conclusions and future research are drawn in Section 4.

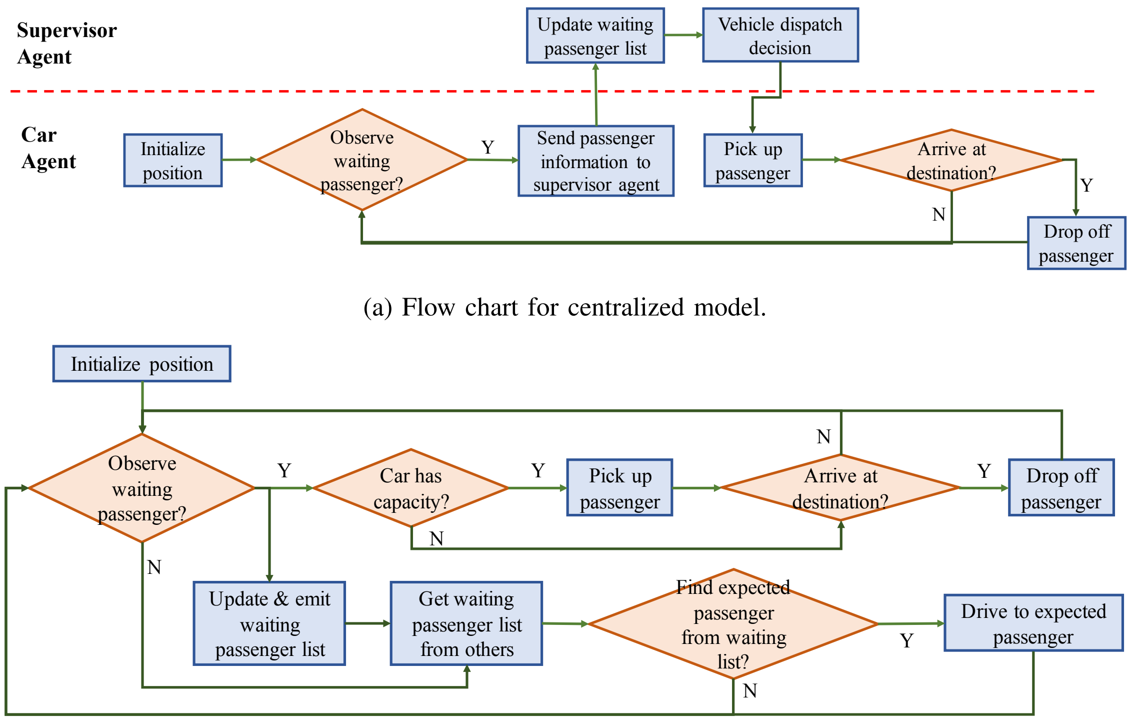
2 MULTI-AGENT MODELING FOR VEHICLE SHARING OPERATION

Due to its advantages to model complex systems, the agent-based simulation has been applied to a wide variety of areas including manufacturing (Shen and Norrie 1999), transportation (Chen and Cheng 2010), economics (Chen et al. 2012), marketing (Negahban and Yilmaz 2014), social sciences (Axelrod 1997), and biological system (Hinkelmann et al. 2011), just to name a few. In this research, we employ the agent-based modeling approach to simulate vehicle sharing operations. Three types of agents are designed which include: 1) supervisor agent, 2) car agent, and 3) passenger agent. The features and behaviors for these three agents are presented in Table 1.

Table 1: Definition of agent features and behaviors.

Agent	**Category**	**Name (Description)**
Car	**Feature**	$f1$: starting point (e.g., [0, 0])
		$f2$: initial time (the time period that the car is available in the system)
		$f3$: current position (e.g., [35, 10])
		$f4$: capacity (# of seats, e.g., 3, 4)
		$f5$: moving direction (e.g., east, west, south, north)
		$f6$: idle time (# of time periods without passengers on board)
		$f7$: on board passengers
		$f8$: waiting passengers (observed passengers that are not picked up)
		$f9$: expected passenger (passengers to pick up)
		$f10$: communication range (e.g., 1 mile, 2 miles)
	Behavior	$b1$: pick up
		$b2$: drop off
		$b3$: U turn
		$b4$: move
		$b5$: get waiting passengers from car itself
		$b6$: get waiting passengers from neighbors
		$b7$: identify expected passengers from the waiting list
Passenger	**Feature**	$f1$: origin (e.g., [0, 0])
		$f2$: destination (e.g., [50, 5])
		$f3$: initial time (the time period that the passenger is available in the system)
		$f4$: current position (e.g., [35, 10])
		$f5$: status (0: waiting, 1: on board, 2: delivered)
		$f6$: car id (ID for the car to pick up the passenger)
		$f7$: on board time
		$f8$: arrival time
	Behavior	$b1$: move (the passengers can only move with a car when they are on board)
Supervisor	**Feature**	$f1$: waiting passengers (all the observed passengers that are not picked up)
		$f2$: available cars (all the cars that are not full)
	Behavior	$b1$: get waiting passengers from all the cars
		$b2$: dispatch available vehicles to pick up waiting passengers

Three vehicle sharing operation models are studied. The first one is a rule-based independent operation model where each vehicle is randomly driven on the road and it will pick up all the observed passengers if it is not full. In this model, the vehicles do not have any communication and information exchange with other vehicles. The second one is a centralized operation model where each vehicle can communicate with a central supervisor agent (see Figure 1a). In this model, the vehicle will record the positions of all the passengers it observes but does not have capacity to pick up. The vehicles will exchange the passenger information with the supervisor agent. To this end, the supervisor agent will have a complete list of all the unsatisfied passenger demand, and it will assign a nearest vehicle to pick up each passenger. In this model, the vehicles fully comply with operation commands from the supervisor agent instead of having intelligence to autonomously operate themselves. The third one is a swarm intelligence based distributed operation model where each vehicle can communicate with other vehicles in its neighborhood (see Figure 1b). Similar to the centralized model, each vehicle will record the positions of all the passenger demands it observes and emit the list of waiting passengers as digital pheromone to the environment which can be sensed by other vehicles in its neighborhood. According to the information received from other vehicles, the vehicle can have a clear understanding about the passenger demands in its local area and can automatically and intelligently make decisions to pick up the nearest passengers.



(a) Flow chart for centralized model.

(b) Flow chart for distributed model.

Figure 1: Vehicle sharing operation models.

Let c, p represent the c^{th} car and the p^{th} passenger, NC and NP represent the number of cars and number of passengers, $t_{c,i}$, $t_{p,0}$, $t_{p,ob}$, and $t_{p,a}$ represent the total idle time for car c, the initial time, on board time and arrival time for passenger p respectively. We propose four metrics to evaluate the performance of these three operation models which include: 1) total number of time steps to deliver all the passengers T (see Eq. (1)), 2) average idle time for all the cars AIT (see Eq. (2)), 3) average waiting time for all the passengers AWT (see Eq. (3)), 4) maximum waiting time for all the passengers MWT (see Eq. (4)). In this study, the passenger's in-vehicle travel time is not affected by the operation mode and car capacity, so we only consider out-of-vehicle waiting time for passengers.

$$T = \max_{p=1,\ldots,NP} t_{p,a}, \tag{1}$$

$$AIT = \frac{\sum_{c=1}^{NC} t_{c,i}}{NC}, \tag{2}$$

$$AWT = \frac{\sum_{p=1}^{NP} \left(t_{p,ob} - t_{p,0}\right)}{NP}, \tag{3}$$

$$MWT = \max_{p=1,\ldots,NP} \left(t_{p,ob} - t_{p,0}\right). \tag{4}$$

The first model, independent operation model, only has two agents, Car and Passenger where the Car agent includes features $f1$-$f7$ and behaviors $b1$-$b4$, and Passenger agent includes all the features and behaviors defined in Table 1. In the centralized model, all the three agents are included. The Car agent includes features $f1$-$f9$ and behaviors $b1$-$b5$, and the Passenger and Supervisor agents include all the features and behaviors. The distributed model only includes Car and Passenger agents which include all the features and behaviors defined in Table 1. In this research, we implement the agent-based simulation model in Mesa due to its powerful build-in core components (e.g., spatial grids, agent schedulers) and browser-based interface to visualize the simulation model. Mesa is an Apache2 licensed agent-based modeling framework in Python.

3 SIMULATION RESULT ANALYSIS

In this section, we compare the performance of three different operation models (independent, centralized, and distributed) under different communication range (*CR*) and car capacity (*Cap*). We assume that there are 50 cars and 100 passengers on a linear corridor with length 100 which has unlimited two-way lanes. All the cars have the same speed, which is one unit distance per one unit time step. The passengers are spatially and temporally distributed on the corridor, and they have the same destination. The car will move forward when there is no passenger on board. The initial time for car and passenger are assumed to follow an uniform distribution on range [1, 10], and the initial position for car and passenger are assumed to follow an uniform distribution on range [0, 90]. The communication range (*CR*) is changed from 1, 10 to 20, and the car capacity (*Cap*) is changed from 1, 2, to 3. Each car is assumed to only communicate with other cars in its neighborhood with distance less than *CR*. This indicates that the car can communicate with more cars when the *CR* is large. Each model is independently run 30 times, and the values of the four metrics in Eqs. (1)-(4) are recorded for comparison.

3.1 Comparison Analysis for the Three Operation Models under Settings of *CR*=10 and *Cap*=2

Table 2: Experimental results for the three operation models (*CR*=10, *Cap*=2).

		Independent	**Centralized**	**Distributed**
T	Average	226.37	215.2 (4.93%)	215.3 (4.89%)
	Maximum	248	236 (4.84%)	239 (3.63%)
	Minimum	171	107 (37.43%)	107 (37.43%)
AIT	Average	70.51	60.95 (13.55%)	60.45 (14.26%)
	Maximum	85.36	75.84 (11.15%)	77.36 (9.37%)
	Minimum	43.22	5.74 (86.72%)	6.64 (84.64%)
AWT	Average	15.34	12.29 (19.87%)	12.07 (21.32%)
	Maximum	31.51	23.78 (24.53%)	21.28 (32.47%)
	Minimum	7.87	6.23 (20.84%)	5.63 (28.46%)
MWT	Average	123.5	113.93 (7.75%)	114.2 (7.53%)
	Maximum	146	134 (8.22%)	137 (6.16%)
	Minimum	96	34 (64.58%)	38 (60.42%)

In this set of experiments, we set CR as 10 and Cap as 2. The average, maximum, and minimum values of T, AIT, AWT, and MWT obtained at each run are presented in Table 2. It is observed that the centralized model performs the best in terms of T and MWT, and the distributed model performs the best in terms of AIT and AWT. The independent model performs the worst in terms of the four metrics.

According to the statistical t-test, we conclude that both centralized and distributed models significantly outperform independent model in terms of AIT, AWT, and MWT. The centralized and distributed models are comparable. Compared to the independent model, the centralized model can improve average values of 1) T by 4.93%, 2) AIT by 13.55%, 3) AWT by 19.87%, and 4) MWT by 7.75%, and the distributed model can improve average values of 1) T by 4.89%, 2) AIT by 14.26%, 3) AWT by 21.32%, and 4) MWT by 7.53%.

3.2 Statistical Comparison of the Distributed Model under Various Settings of *CR* and *Cap*

In this set of experiments, the performances of the distributed model are compared under different values of *CR* and *Cap*. Please note the independent and centralized models do not have parameter *CR*, so we do not compare these two models under various settings of *CR*. The box plots for the distributed model in terms of AWT under various settings of *CR* and *Cap* are shown in Figure 2 where the mean value over the 30 runs is represented using triangle and the outlier is represented using circle. It is demonstrated that 1) the performance of the distributed model is not impacted by the communication range when the car capacity is 1, 2) when the car capacity is increased to 2 and 3, the distributed model under *CR*=10 and *CR*=20 performs better than the model under *CR*=1, and 3) the performances of the distributed model under *CR*=10 and *CR*=20 are comparable.

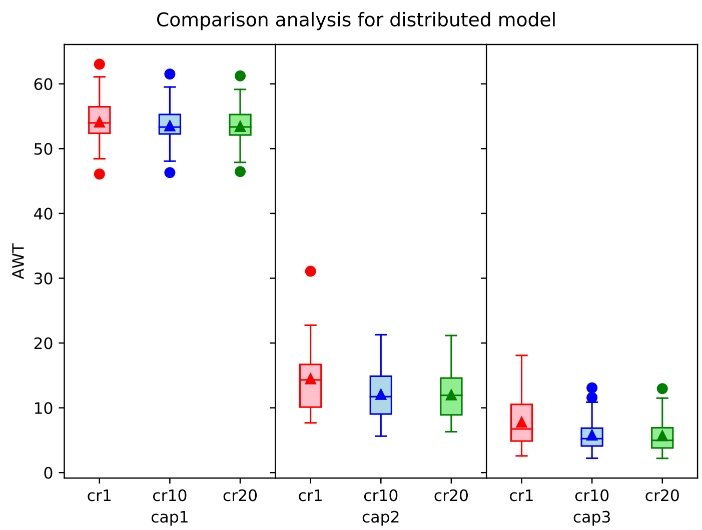


Figure 2: Box plots of AWT for the distributed model under various settings of *CR* and *Cap*.

The statistical t-test results for the distributed model under various settings of *CR* and *Cap* are presented in Table 3 where the model is ranked based on the t-test results. The model A will be assigned symbols (">>", ">", or "=") based on the following rules: 1) symbol ">>" if it is significantly better than model B (e.g., p-value < 0.05), 2) symbol ">" if it is better than model B (e.g., p-value is in the range [0.05, 0.90]), 3) symbol "=" if it performs the same as model B (e.g., p-value > 0.90). The two symbols of the rank #1 model indicate its relationship between the rank #2 and rank #3 models, and the symbol of the rank #2 model indicates its relationship with the rank #3 model. When *Cap*=1, the distributed model under *CR*=20 performs better than $CR = 10$, and better than $CR = 1$. However, there does not exist significant difference among these three values of *CR*. When *Cap*=3, the distributed model under *CR*=20 and *CR*=10 significantly outperforms the model under *CR*=1. Under all the three values of *Cap*, the performances of the distributed model under *CR*=10 and *CR*=20 are comparable. We can conclude that the performance of distributed model can be improved by increasing the communication range. The cars can communicate with more cars in their neighborhood when the communication range is increased which can significantly improve the intelligence of car and to better match the passenger demands.

Table 3: Statistical t-test results for the distributed model under various settings of *CR* and *Cap*.

Cap	**Ranking**	***T***	***AIT***	***AWT***	***MWT***
	#1	20 (>, >)	20 (>, >)	20 (=, >)	20 (>, >)
1	#2	10 (>)	10 (>)	10 (>)	10 (>)
	#3	1	1	1	1
	#1	10 (=, >)	10 (>, >)	20 (=, >>)	10 (>, >)
2	#2	20 (>)	20 (>)	10 (>>)	20 (>)
	#3	1	1	1	1
	#1	20 (>, >>)	20 (>, >>)	20 (>, >>)	20 (>, >>)
3	#2	10 (>>)	10 (>>)	10 (>>)	10 (>>)
	#3	1	1	1	1

3.3 Statistical Comparison of the Three Models under Various Settings of *Cap*

In this set of experiments, the performances of all three models are compared under different values of *Cap*. The box plots for these three models are shown in Figures 3-5. It is observed that the performances of all the three models are significantly improved when the car capacity is changed from 1, 2, to 3. For these three models, the difference between *Cap*=1 and *Cap*=2 is greater than the difference between $Cap = 2$ and $Cap = 3$.

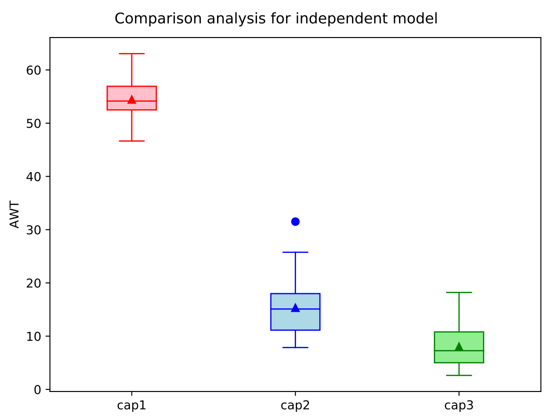


Figure 3: Box plots of *AWT* for the independent model under various settings of *Cap*.

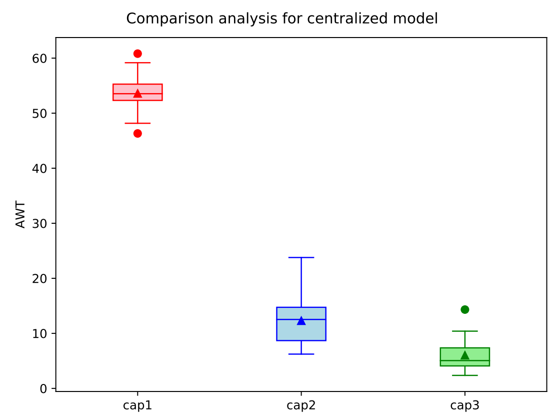


Figure 4: Box plots of *AWT* for the centralized model under various settings of *Cap*.

The statistical t-test results for these three models under various settings of *Cap* are presented in Table 4. Increasing the car capacity can significantly improve the performance of all the three vehicle sharing operation models. It is concluded that the vehicle sharing system will be more efficient when more cars or cars with large capacity collaborate with others to share information.

3.4 Statistical Comparison of the Three Models under Various Settings of *CR* and *Cap*

In this set of experiments, the performances of the three models are compared under different values of *CR* and *Cap*. The box plots for these three algorithms are shown in Figures 6-8. When *Cap*=1, there does not exist significant difference among the three models, and the centralized model performs the best.

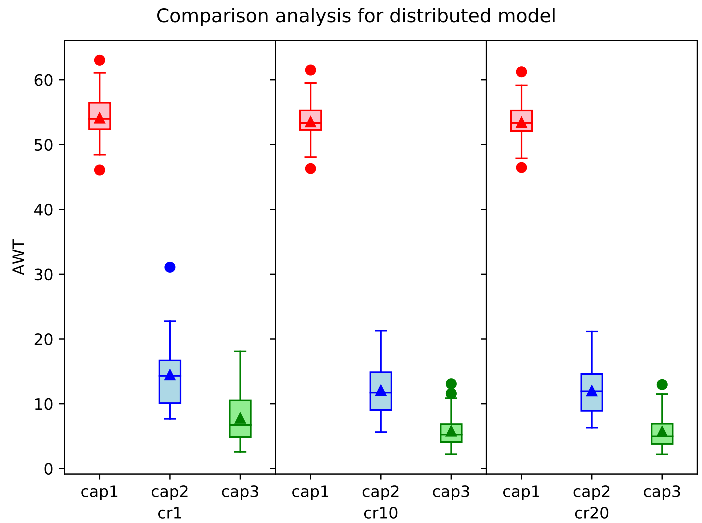


Figure 5: Box plots of *AWT* for the distributed model under various settings of *Cap*.

Table 4: Statistical t-test results for the three models under various settings of *Cap*.

Model	***CR***	**Ranking**	***T***	***AIT***	***AWT***	***MWT***
		#1	3 (>>, >>)	3 (>, >>)	3 (>>, >>)	3 (>>, >>)
Independent		#2	2 (>>)	2 (>>)	2 (>>)	2 (>>)
		#3	1	1	1	1
		#1	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)
Centralized		#2	2 (>>)	2 (>>)	2 (>>)	2 (>>)
		#3	1	1	1	1
		#1	3 (>>, >>)	3 (>, >>)	3 (>>, >>)	3 (>>, >>)
	1	#2	2 (>>)	2 (>>)	2 (>>)	2 (>>)
		#3	1	1	1	1
		#1	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)
Distributed	10	#2	2 (>>)	2 (>>)	2 (>>)	2 (>>)
		#3	1	1	1	1
		#1	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)	3 (>>, >>)
	20	#2	2 (>>)	2 (>>)	2 (>>)	2 (>>)
		#3	1	1	1	1

When *Cap*=2, the centralized and distributed models perform better than the independent model, and the centralized model performs better than the distributed model when the communication range is small (e.g., 1). The performance of these three models under *Cap*=3 is similar to *Cap*=2. The distributed model can outperform the centralized model when the communication range is increased (e.g., 10, 20).

The statistical t-test results for these three models under various settings of *CR* and *Cap* are presented in Table 5. It is observed that both the centralized and distributed models perform significantly better than the independent model when car capacity is greater than 1. This is due to the fact that the cars can be more optimally dispatched when they can exchange information with others and have more capacities. The centralized model performs significantly better than the distributed model when car capacity is large (e.g., 3) and communication range is small (e.g., 1). In the centralized model, we assume all the cars can communicate with the supervisor agent, so its performance is independent to the communication range.

Table 5: Statistical t-test results for the three models under various settings of *CR*.

Cap	***CR***	**Ranking**	***T***	***AIT***	***AWT***	***MWT***
		#1	Cen. (>, >)	Cen. (>, >)	Cen. (>, >)	Cen. (>, >)
	1	#2	Ind. (>)	Dis. (>)	Dis. (>)	Ind. (>)
		#3	Dis.	Ind.	Ind.	Dis.
		#1	Cen. (>, >)	Cen. (>, >)	Dis. (=, >)	Cen. (>, >)
1	10	#2	Ind. (=)	Dis. (>)	Cen. (>)	Ind. (=)
		#3	Dis.	Ind.	Ind.	Dis.
		#1	Cen. (>, >)	Dis. (>, >)	Dis. (>, >)	Cen. (>, >)
	20	#2	Dis. (=)	Cen. (>)	Cen. (>)	Dis. (>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Cen. (>, >)	Cen. (>, >>)	Cen. (>, >>)	Cen. (>, >>)
	1	#2	Dis. (>)	Dis. (>)	Dis. (>)	Dis. (>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Cen. (=, >)	Dis. (=, >>)	Dis. (>, >>)	Cen. (=, >>)
2	10	#2	Dis. (>)	Cen. (>>)	Cen. (>>)	Dis. (>>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Cen. (=, >)	Cen. (=, >>)	Dis. (>, >>)	Cen. (>, >>)
	20	#2	Dis. (>)	Dis. (>>)	Cen. (>>)	Dis. (>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Cen. (>>, >>)	Cen. (>>, >>)	Cen. (>>, >>)	Cen. (>>, >>)
	1	#2	Dis. (>)	Dis. (>)	Dis. (>)	Dis. (>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Dis. (>, >>)	Dis. (>, >>)	Dis. (>, >>)	Dis. (>, >>)
3	10	#2	Cen. (>>)	Cen. (>>)	Cen. (>>)	Cen. (>>)
		#3	Ind.	Ind.	Ind.	Ind.
		#1	Dis. (>, >>)	Dis. (>, >>)	Dis. (>, >>)	Dis. (>, >>)
	20	#2	Cen. (>>)	Cen. (>>)	Cen. (>>)	Cen. (>>)
		#3	Ind.	Ind.	Ind.	Ind.

However, the cars can communicate with less cars when the communication range is decreased in the distributed model. The performance of distributed model will be very similar to the independent model when the communication range is small. The distributed model can perform better than the centralized model for large communication range and car capacity. When both the communication range and car capacity are large, the cars will have more flexibility to respond to system dynamics using the distributed model and can achieve better performance comparing to the centralized model.

4 CONCLUSION

In this research, we have developed an agent-based simulation model to study the vehicle sharing operation. Three operation models have been implemented which include: 1) independent operation model where vehicles are isolate and always pick up the passengers they observe, 2) centralized operation model where all the vehicles can record a list of the observed passengers that are in the waiting status, and are controlled by a supervisor agent, and 3) distributed operation model where the vehicles can maintain a list of observed waiting passengers and share this information with other vehicles in their neighborhood, and independently operate themselves based on the collected passenger demand information. The three models have been compared using four different metrics: 1) total time steps to deliver all the passengers, 2) average idle time

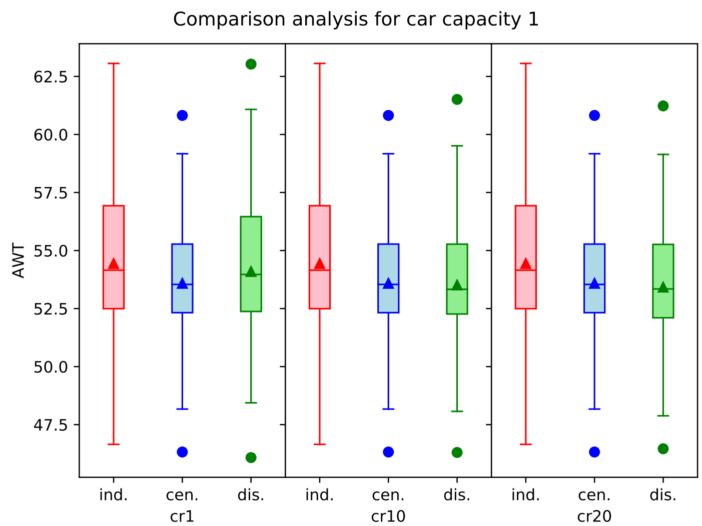


Figure 6: Box plots of AWT for the three models under Cap=1.

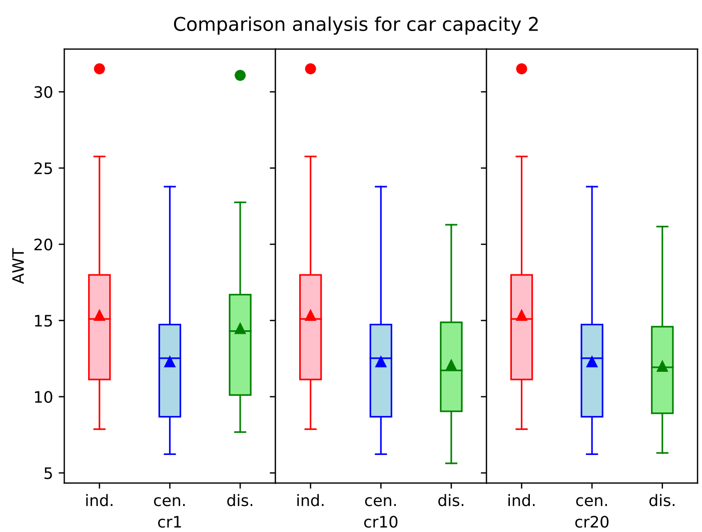


Figure 7: Box plots of AWT for the three models under Cap=2.

for all the vehicles, 3) average waiting time for all the passengers, and 4) maximum waiting time for all the passengers. The simulation results demonstrate that: 1) the distributed model prefers large communication range, 2) all the three models prefer large car capacity, 3) distributed and centralized models significantly perform better than the independent model when car capacity is greater than 1, and 4) centralized model significantly performs better than distributed model when car capacity is large and communication range is small. These results can provide valuable insights to determine communication range and car capacity for large scale vehicle sharing problem.

In the future study, we will extend the agent-based simulation model to consider limited lanes on the corridor and multi-ways corridor. Some advanced passenger demand prediction models (e.g., deep learning models) will be developed to accurately predict the passenger demand. More intelligent operation decision models will be developed to optimally operate the vehicle sharing system, and the performance of the centralized and distributed models will be compared using large-scale vehicle sharing operation problem.

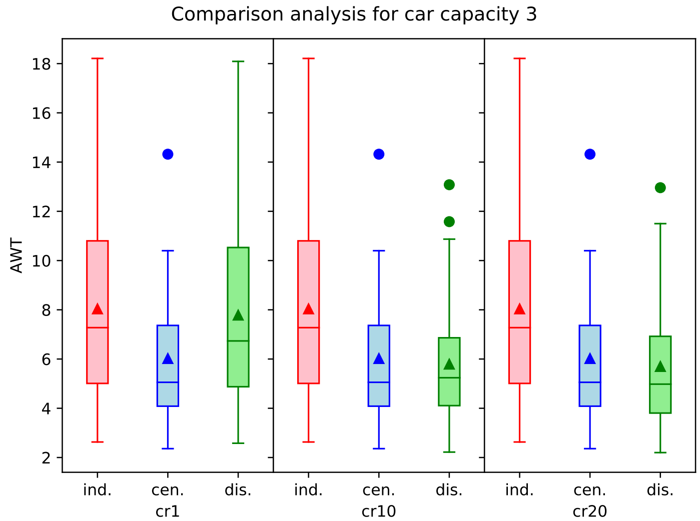


Figure 8: Box plots of *AWT* for the three models under *Cap*=3.

REFERENCES

Atzori, L., A. Iera, and G. Morabito. 2010, oct. "The Internet of Things: A survey". *Computer Networks* 54 (15): 2787–2805.

Axelrod, R. 1997. "Advancing the Art of Simulation in the Social Sciences BT - Simulating Social Phenomena". In *Economics and Mathematical Systems*, edited by R. Conte, R. Hegselmann, and P. Terna, 21–40. Berlin, Heidelberg: Springer Berlin Heidelberg.

Barth, M., and M. Todd. 1999, aug. "Simulation model performance analysis of a multiple station shared vehicle system". *Transportation Research Part C: Emerging Technologies* 7 (4): 237–259.

Bureau of Transportation Statistics 2014. "Pocket guide to transportation". Technical report, U.S. Department of Transportation, Washington, DC.

Chen, B., and H. H. Cheng. 2010. "A Review of the Applications of Agent Technology in Traffic and Transportation Systems". *IEEE Transactions on Intelligent Transportation Systems* 11 (2): 485–497.

Chen, S.-H., C.-L. Chang, and Y.-R. Du. 2012. "Agent-based economic models and econometrics". *The Knowledge Engineering Review* 27 (2): 187–219.

Ciari, F., M. Balmer, and K. W. Axhausen. 2009. "Concepts for Large-Scale Carsharing System: Modeling and Evaluation with Agent-Based Approach". In *88th Annual Meeting Transportation Research Board*.

Dasgupta, P. 2008. "A Multiagent Swarming System for Distributed Automatic Target Recognition Using Unmanned Aerial Vehicles". *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 38 (3): 549–563.

Du, Y., and R. Hall. 1997, feb. "Fleet Sizing and Empty Equipment Redistribution for Center-Terminal Transportation Networks". *Management Science* 43 (2): 145–157.

Ford, H. J. 2012. *Shared Autonomous Taxis: Implementing an Efficient Alternative to Automotive Dependency*. Ph. D. thesis, Department of Operations Research and Financial Engineering, Princeton University, Princeton, NJ.

Hinkelmann, F., D. Murrugarra, A. S. Jarrah, and R. Laubenbacher. 2011. "A Mathematical Framework for Agent Based Models of Complex Biological Networks". *Bulletin of Mathematical Biology* 73 (7): 1583–1602.

Jennergren, P. 1973, sep. "A Price Schedules Decomposition Algorithm for Linear Programming Problems". *Econometrica* 41 (5): 965–980.

Klusch, M., and A. Gerber. 2002. "Dynamic Coalition Formation among Rational Agents". *IEEE Transactions on Intelligent Systems* 17 (3): 42–47.

Laporte, G., F. Meunier, and R. Wolfler Calvo. 2015. "Shared mobility systems". *4OR* 13 (4): 341–360.

Li, X., J. Ma, J. Cui, A. Ghiasi, and F. Zhou. 2016, jun. "Design framework of large-scale one-way electric vehicle sharing systems: A continuum approximation model". *Transportation Research Part B: Methodological* 88:21–45.

Litman, T. 2007. "Parking Management: Comprehensive Implementation Guide". Technical report, Victoria Transport Policy Institute, Victoria, BC, Canada.

Millard-Ball, A., G. Murray, J. T. Schure, C. Fox, and J. Burkhardt. 2005. "Car-Sharing: Where and how it succeeds". Technical report, Nelson Nygaard Consulting Associates, San Francisco, CA.

Negahban, A., and L. Yilmaz. 2014. "Agent-based simulation applications in marketing research: an integrated review". *Journal of Simulation* 8 (2): 129–142.

Pérez-Lombard, L., J. Ortiz, and C. Pout. 2008. "A review on buildings energy consumption information". *Energy and Buildings* 40 (3): 394–398.

Sandholm, T. W. 1998. "Contract Types for Satisficing Task Allocation: I Theoretical Results". In *AAAI Spring Symposium Series*. Department of Computer Science; Washington University.

Shaheen, P., and A. Cohen. 2013. "Innovative Mobility Carsharing Outlook". Technical report, University of Berkeley, California, Berkeley, CA.

Shen, W., and D. H. Norrie. 1999. "Agent-Based Systems for Intelligent Manufacturing: A State-of-the-Art Survey". *Knowledge and Information Systems* 1 (2): 129–156.

Shoup, D., and M. Manville. 2005, dec. "Parking, People, and Cities". *Journal of Urban Planning and Development* 131 (4): 233–245.

Sinha, K. C. 2003. "Sustainability and urban public transportation". *Journal of Transportation Engineering* 129 (4): 331–341.

Tappeta, R. V., and J. E. Renaud. 1997. "Multiobjective Collaborative Optimization". *Journal of Mechanical Design* 119 (3): 403–411.

Uesugi, K., N. Mukai, and T. Watanabe. 2007. "Optimization of Vehicle Assignment for Car Sharing System". *Knowledge-based intelligent information and engineering systems* 4693:1105–1111.

Xiao, A., S. Zeng, J. K. Allen, D. W. Rosen, and F. Mistree. 2005. "Collaborative multidisciplinary decision making using game theory and design capability indices". *Research in Engineering Design* 16 (1-2): 57–72.

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