

2021

An Ant-based Intelligent Design for Future Self-driving Commercial Car Service Strategy

Jian Denny Lin

University of Houston-Clear Lake, linjian@uhcl.edu

Naveed Saleem

University of Houston - Clear Lake, saleem@uhcl.edu

Vance Allen Etnyre

University of Houston-Clear Lake, etnyre@uhcl.edu

Gokhan Gercek

University of Houston - Clear Lake, gercek@uhcl.edu

Nanfei Sun

University of Houston Clear Lake, sun@uhcl.edu

Follow this and additional works at: <https://scholarworks.lib.csusb.edu/jitim>



Part of the [Business Intelligence Commons](#), [Management Information Systems Commons](#), and the [Technology and Innovation Commons](#)

Recommended Citation

Lin, Jian Denny; Saleem, Naveed; Etnyre, Vance Allen; Gercek, Gokhan; and Sun, Nanfei (2021) "An Ant-based Intelligent Design for Future Self-driving Commercial Car Service Strategy," *Journal of International Technology and Information Management*: Vol. 29: Iss. 3, Article 5.

DOI: <https://doi.org/10.58729/1941-6679.1422>

Available at: <https://scholarworks.lib.csusb.edu/jitim/vol29/iss3/5>

This Article is brought to you for free and open access by CSUSB ScholarWorks. It has been accepted for inclusion in *Journal of International Technology and Information Management* by an authorized editor of CSUSB ScholarWorks. For more information, please contact scholarworks@csusb.edu.

An Ant-based Intelligent Design for Future Self-driving Commercial Car Service Strategy

*Jian (Denny) Lin, Naveed Saleem, Vance Allen Etnyre¹,
Gokhan Gercek, Nanfei Sun*

*Management Information Systems
University of Houston – Clear Lake
Houston, TX 77058, USA*

ABSTRACT

The technology of self-driving cars will inevitably change the industry of taxis and ride-sharing cars that provide important commercial ground transportation services to travelers, tourists and local residents. There is no doubt that new techniques, business models and strategies will be needed to follow the use of self-driving cars. This paper focuses on a forward-looking research topic that route commercial, vacant self-driving vehicles so that the values to both businesses and passengers are improved. Importance of solutions to the new problem is discussed. We also propose a novel design which simulates behaviors of ants in nature to the vehicles. The goal of the system is to obtain an overall balance between the demands of using the services from the passengers and availability of the vehicles in all service areas. The system not only uses historical data to make decisions, it also responds promptly for demands appeared dynamically.

Keywords: Self-driving car, ant colony optimization, algorithms

¹ The work was done before the author's retirement

INTRODUCTION

As in 2019, a revolutionary technology that may completely change our life and business society has been clearly seen: self-driving cars.

A self-driving car, also known as an autonomous car or a driverless car, is a vehicle that is capable of sensing its environment and navigating without much human input [Gehrig and Stein, 1999]. In the past decades, important milestones have been completed which indicate an inevitable future of self-driving cars for our transportation. In 1992, a Carnegie Mellon researcher Dean Pomerleau described in his Ph.D. thesis that it is possible to control a vehicle without a driver by taking images from the roads and using the technology of neural network [Pomerleau, 1992]. When entering into the new century, Google began their self-driving vehicle project in 2009, now called Waymo. After experiments of operating their autonomous cars for 300,000 miles, in 2014 Waymo revealed a prototype of a 100% autonomous car without any steering wheel, gas pedal or brake pedal. In 2017, Waymo's fully self-driving cars had arrived and their fully self-driving vehicles began test-driving on public roads without anyone in the driver's seat. Based on what Waymo said as in 2018, they partnered with Jaguar to create the world's first premium electric self-driving vehicle: Jaguar I-PACE. They will start testing these vehicles in 2019 and will add up to 20,000 I-PACEs to Waymo's fleet in the next few years. Soon, members of the public will get to use these vehicles in their daily lives [Waymo]. The use of self-driving cars can bring significant benefits to people and our society such as reducing car accidents, freeing people from driving so that people can work during a ride, less traffic congestions, and lower fuel consumption.

Many pioneer companies have started to work with autonomous transportation to make a big change to the industry of commercial car services, such as taxis and ride-sharing vehicles (e.g., Uber). In 2017, Waymo launched a program called Early Rider Program. They invited residents in Phoenix, USA to join a public trial of their self-driving vehicles. As an early rider, the participants will be able to use their self-driving cars to go places they frequent every day. Also, Waymo recently filed an application to the Department of Motor Vehicles (DMV) to request a permit to operate 52 autonomous, fully-driverless vehicles in California. Uber, although it was involved into a fatal accident, their self-driving car test was continued in July 2018 back on public roads in Pittsburgh, USA. In Asia, August 2018 the first self-driving taxi has successfully taken paying passengers on the streets in Tokyo. The project is developed by ZMP, a developer of autonomous driving technology, and the taxi company Hinomaru Kotsu. There is a prospect that the service will be ready during the 2020 Tokyo Summer Olympics. In Europe, almost at the same time a Russian tech giant Yandex has announced the launch of Europe's first self-driving taxi, which will be tested soon in Innopolis, Russia.

There is no exception that every time an adoption of a new technology inspires researchers to develop new solutions in different applications or systems.

In this paper, we are interested in a forward-looking research topic from the use of self-driving vehicles in commercial services. While drivers are removed from operating the vehicles, how to route the vehicles when they are vacant is not a trivial problem. Generally, promptly moving vacant vehicles to places in need will bring benefits to both passengers and businesses providing the service. The decisions of where to move the vehicles depend on several factors such as predicted demands in areas and traffic conditions in those areas. In the following sections, we present a strategy which is inspired by ants' behavior to route the vacant vehicles, so that average passenger waiting time and vehicle vacant time are significantly reduced.

The rest of the paper is organized as follows. Next section discusses a literature review. Section 3 provides data analysis from a real-world data set to show the importance of the solutions of the problem. Section 4 presents our design to solve the problem. In section 5, simulation results are shown. The last section summarizes and concludes the work.

LITERATURE REVIEW

In this section, we firstly have a brief review of existing works designed for taxis and ride-sharing cars with drivers. Then, we discuss the reasons why these solutions are not appropriate for self-driving vehicles.

Presently, taxis and ride-sharing cars usually provide services to passengers in the following three ways.

- Taxi drivers cruise with their vehicles on the streets to pick up the passengers they find through luck and experience.
- Passengers use software on their cell phone (app) to call for a vacant vehicle nearby.
- In some cities, taxis and ride-sharing cars wait and queue at a certain place to pick up passengers, for example, an airport or a train station.

As of today, a decision of where to go to pick up the next passenger is primarily made by the driver, who may have a secondary information system for recommendation. Recommendations to help a driver to find the best route has drawn much attention from researchers, either to minimize the vacant time of a vehicle or to maximize the business profit of the driver. Most of the existing works

are designed based on real-world GPS trajectories which were collected through a large number of probing taxis [Alves et al., 2010; Adomavicius and Tuzhilin, 2005; Wei et al., 2012; Yuan et al., 2010; Yuan et al., 2013; Zhang et al., 2013; Zhang et al., 2012]. By using the historical data, knowledge and strategies of the best practice are mined from the data.

For example, passenger search strategies of high-profit taxi drivers are analyzed in [Yuan et al., 2011; Zhang et al., 2015; Lee et al., 2008]. From the analysis, hot spots for customer pick-ups are learned from the GPS trajectories and the locations are clustered into multiple representative small areas. When a driver requests a route recommendation, a sequence of pick-up points is provided as driving directions. Instead of just providing the near hot spots, some other researchers design recommendation systems to provide drivers with detailed driving routes so that the likelihood of picking up a passenger on the routes is maximized [Qu et al., 2014; Ding et al., 2013; Ge et al., 2010; Hu et al., 2012]. For example, in [Qian et al., 2012; Yu et al., 2019; Rong et al., 2016] the optimal routing problem is modeled as a Markov decision process to derive the most rewarding driving paths in a long run. The routing recommendation problem is also discussed in ride-sharing. In [Lin et al., 2018], the authors consider the problem of exploring travel demand statistics to optimize ride-sharing routing, in which the driver of a vehicle determines a route to transport multiple customers with similar itineraries and schedules in a cost-effective and timely manner.

All of the above works focus on finding solutions for a single vacant vehicle's driver to achieve some goals. In [Wardrop 1952], the author points out that each driver in a traffic network non-cooperatively seeks routes to benefit himself the most, which is still true today. In general, there is a conflict between a driver's interest and an overall interest. In a city, there may be several crowded places where are hot spots to pick up passengers. However, while a route or a spot is recommended to multiple drivers, the chances of picking up a passenger by the drivers using the same recommendation may be reduced greatly. Simultaneously, the waiting time of passengers at other locations may be increased. There are some works in literatures considering the competitive among drivers such as the SCRAM approach proposed in [Qian et al., 2015]. SCRAM addresses the route recommendation problem for a group of competing taxi drivers, rather than a single one. A concise route assignment mechanism is designed to guarantee the recommendation fairness for taxi drivers. However, the work only considers a cooperation in a small group which is far from maximizing the overall benefit. Also, the SCRAM approach works passively as it only provides recommendation to drivers who request one. Agent-based model has been used to solve a lot of research problems in information systems. In [Grau and Romeu, 2015], the agent-based model is used to obtain the

optimum number of vehicles and performance indicators of the provision of taxi services under the dispatching operation mode

While the works we discussed by far are done for vehicles with drivers, recently researchers have started to explore the routing problems with self-driving vehicles such as the one in [Shalamov et al., 2019].

However, the work is still in the scope of finding a route for a single taxi. It is clearly that there is a need of new approaches in which all vehicles are routed collectively to enhance the overall benefit.

MOTIVATIONS AND PRELIMINARY WORKS

Traffic is a dynamic system so that an effective and efficient placement of vacant vehicles depends on an accurate estimation of demands of requesting the service. It is known that similar demand patterns are repeating daily or weekly. At a specific time, a location where a lot of taxis or ride-sharing cars drop off passengers may not be a location where they pick up passengers. The unbalancing clearly creates inefficiency. Recently, in many big cities such as New York, Beijing and Singapore, taxis are equipped with GPS sensors and these taxis send data to a data center at a certain frequency. A large number of data including GPS trajectories, occupancy and fare information are being collected every day. The data can be used to study the car-use demand patterns in different locations and different time slots.

The following figures are created from the data of New York City (NYC) taxis which can be accessed publicly at [NYC Taxi & Limousine Commission - TLC Trip Record Data]. Figure 1 and Figure 2 show a heat map of numbers of passenger pick-ups and drop-offs of a day from 8:00 to 18:59 in NYC, respectively. The two figures show that the Manhattan area is the busiest area. There exists an unbalancing of the pick-ups and drop-offs in the areas surrounding Manhattan. To take a closer look at the area of Manhattan, Figure 3 shows a heat map of the numbers of pick-ups with a 10-minute time slot starting at 08:30 where Figure 4 shows a heat map of the numbers of drop-offs in the same time slot. It can be seen that during the time slot a lot of arrivals or drop-offs happen in the area of Midtown (just below the Central Park in the map). However, at the same time the pick-ups scatter more evenly over the area. It is easily to see that a good decision is to send some of the vacant taxis in Midtown to its surrounding areas. In our analysis, some other patterns exist in other time slots. We do not show all of the heat maps due to a limit of the pages.

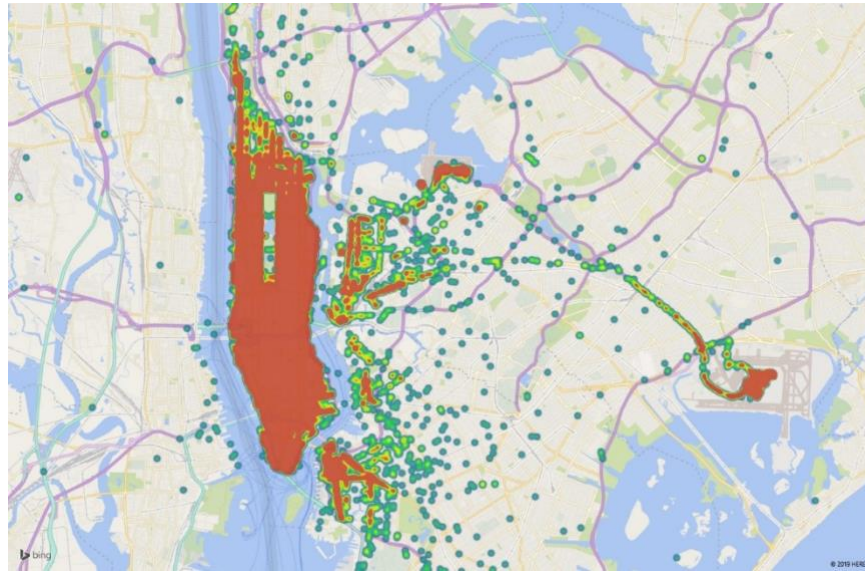


Figure 1. A Heat Map of Number of pick-ups in NYC

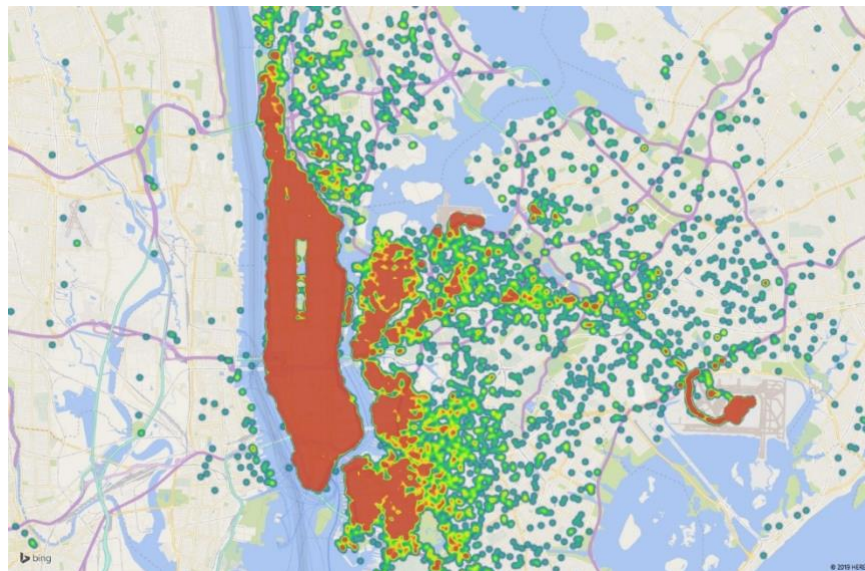


Figure 2. A Heat Map of Number of Drop-offs in NYC

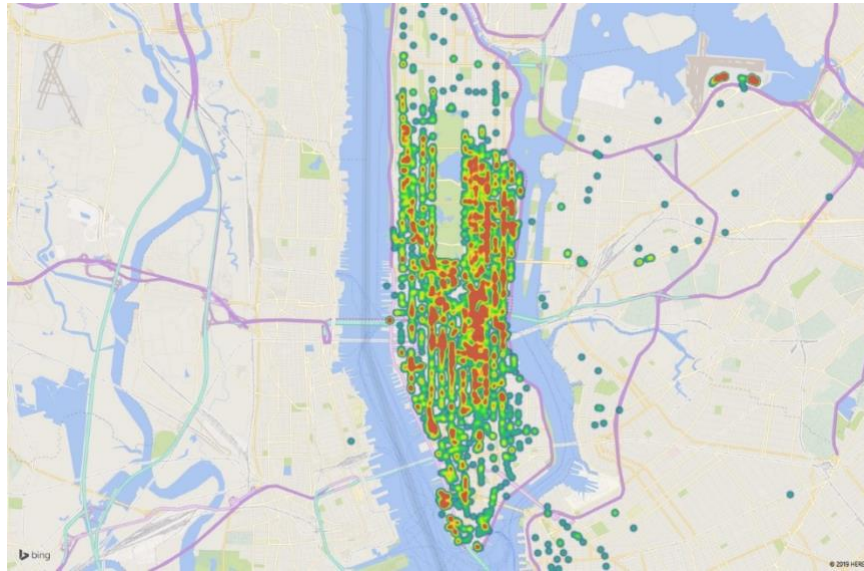


Figure 3. A Heat Map of Number of Pick-ups in Manhattan at 08:30

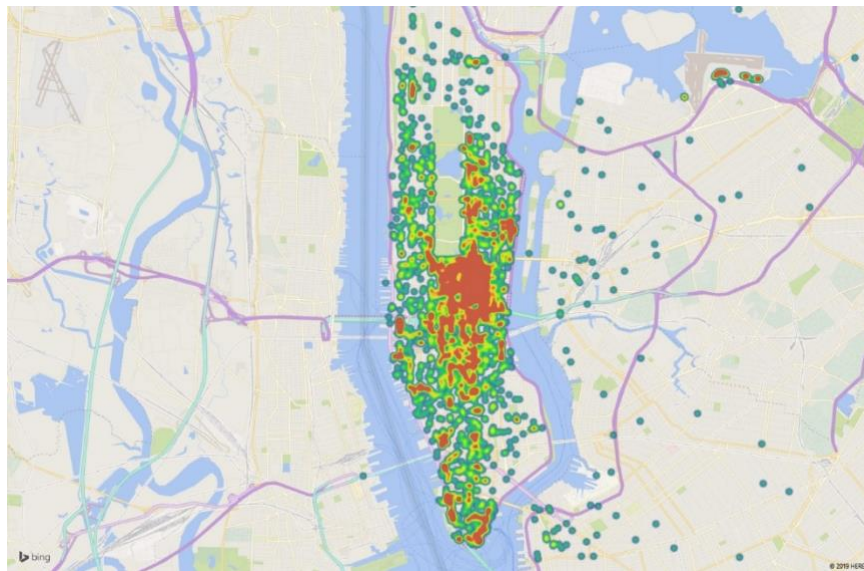


Figure 4. A Heat Map of Number of Drop-offs in Manhattan at 08:30

A service-demand model can be statically built by using a data set that contains historical data, such as the locations where passengers get on and get off the cars.

However, sudden demands can rise in a variety of cases such as poor weather, traffic jams or events like concerts or sport games. A good strategy should not only focus on historical data, but also responds promptly to a real-time change of demand. In next section, we introduce a design based on ant behaviors. We show that its stochastic process is automatic and good to accommodate both static and dynamic demands.

AN ANT-BASED INTELLIGENT

System Model

In this section, we present our design to move vacant, self-driving vehicles in different areas so that it increases efficiency and reduces passengers' waiting time. We consider an urban traffic network modeled as a bi-directed, weighted graph, $G \triangleq (V, E)$. Areas are represented by the vertex set V . The roads connecting the areas are represented by the edges set E . For each $v \in V$, there is a weight associated with it which indicates the passengers' service demand in that area. The weight varies from time to time because the demand is a time-dependent variable. For each $e \in E$, it is associated with two vertexes, v_i and v_j , where e is a path from v_i to v_j . A weight associated with a path represents the travel time from v_i to v_j . The travel time is a dynamic variable and its value depends on a real-time traffic condition.

Each vehicle has a GPS equipped and it can communicate with a central control system using a wireless network. When a vehicle is vacant, it reports its location to the central system and receives instructions for where to move. The system makes decisions based on different factors including real-time service demands, historical data, traffic conditions and so on. The objective of the system is to provide a balance between the availability of vacant vehicles and the demands of requesting service in different areas.

The Ant-Based Approach

Ant Colony Optimization (ACO) is a probabilistic approach for solving computational problems, inspired by the behavior of ants seeking a path between their colony and a source of food. In the nature world, ants of some species initially wander randomly to search food. When the ants find food, they will return to their colony. The ants lay down pheromone trails on the paths they traversed. Other ants later will follow the trails, attracted by the deposited pheromone, to find food. These ants also deposit pheromone trails on the paths. Over time, the pheromone trails start to evaporate.

The pheromone density on a short path becomes higher than the one on a long path because ants traversed on the short path more quickly and more frequently. It in turn will attract more ants to use the short path. Finally, the shortest path between the colony and the source of food is found by the ants (Figure 5).

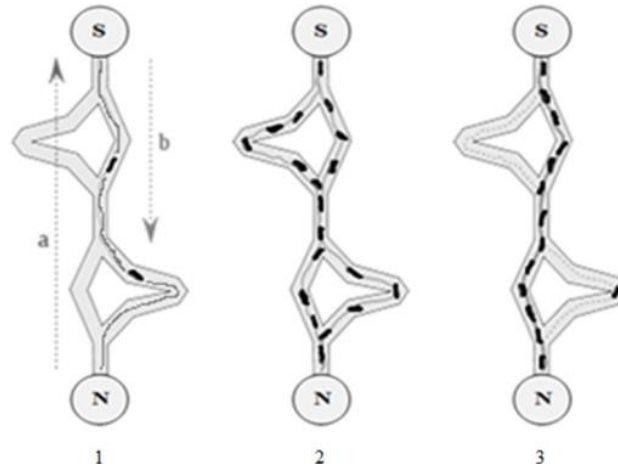


Figure 5. How Ants Find the Shortest Path

The idea of the ACO algorithm is to mimic the way where the ants use pheromone trails to communicate to find the shortest path. Artificial ants are created and walk around a graph representing an optimization problem. When an artificial ant finds a good solution, it will let other ants know the good feedback which will eventually attract more ants to explore in the solution space from the good one.

Evaporation is simulated to avoid the convergence to a locally optimal solution.

Although our problem is not a static combinatorial optimization problem, similarities can be found between it and an ant system. Each vacant vehicle is similar to an ant that faces a decision to find a path to walk. How soon the vehicle will pick up the next passenger is uncertain but there exists statistically significant difference among different paths it can use. Overall, we want more vehicles to go to busier or more crowded areas but the low-demand areas should not be completely ignored. The idea of using the pheromones in the ACO approach can be used to achieve the goal here as well. A density of the pheromone on a path from v_i to v_j can be evaluated by using the service demands on v_i and v_j . If v_j has a higher service demand, it will attract more vehicles from v_i to v_j , or vice versa. Service demands vary dynamically over time as evaporation happens on pheromone trails with different rates. The pheromones trails are updated with a certain frequency based on real-time information and historical data for different time slots.

Every vacant vehicle uses the pheromone trails to decide where it moves to.

The detailed design of creating the artificial pheromone trails is described as follows. Time is divided into slots with a certain length, e.g. 10 minutes. For each area, a normalized value of a static passenger-service demand is obtained from historical data for each time slot. For each pair of areas with roads connected, an expected travel time is calculated from real-time traffic information for both directions, respectively. A real-time demand in an area is also estimated too. The estimated demand can be obtained by using different methods such as calculating an exact number of pick-ups or vacant vehicles in that area at the time. For examples, if the number of pick-ups is significantly higher than the historical data, it may indicate a real-time rise of demands in that area. All of these values together are used to calculate a probability of how to move for a vacant vehicle. Suppose that a vacant vehicle is in an area v_i which connects with n areas, the vehicle has $n+1$ options to move, including the option of roaming in the same area. The probability for the vehicle moving from v_i to v_j at time slot t where v_j is a neighbor area of v_i or $j = i$, is calculated as:

$$p_{ij}^t = \frac{(\tau_j^{t+\Delta t_{ij}})^\alpha (\delta_j^t)^\beta (\theta_{ij}^t)^\vartheta}{\sum_{z \in neighbor_i \cup i} (\tau_z^{t+\Delta t_{iz}})^\alpha (\delta_z^t)^\beta (\theta_{iz}^t)^\vartheta} \quad (1)$$

In the formula, τ is the static service demand and Δt_{ij} is the estimated travel time from v_i to v_j . δ is the current, real-time demand at v_j . θ is a value related to Δt_{ij} that imposes a negative impact to the calculated probability. A long travel time from v_i to v_j will reduce the probability to move from v_i to v_j . In a calculation, we can use a normalized value of $\frac{1}{\Delta t_{ij}}$ for θ in the formula. α , β and ϑ are weights of τ , δ and θ , respectively. At each update time instance, all of the three values, α , δ and θ , are updated. Each vacant vehicle communicates with the central control system to receive instructions for its routing. Once a decision is made, a vehicle may or may not change the decision before it reaches its destination, depending on the implementation of the strategy.

EXPERIMENTAL SIMULATIONS

Experimental Settings

We use the NYC taxi and FHV (For Hire Vehicle) data set [NYC Taxi and Limousine Commission - TLC Trip Record Data] to create testing models used in our simulations. The data set contains tabular data in which each record is for a trip of a vehicle. A record contains fields of pick-up and drop-off locations, date and time, fare, and type of a trip.

By grouping and summarizing the values, it can know where passengers come from and where they go. Then, a historical service demand model based on the different areas can be built. We focus on Manhattan area because it has the biggest number of passenger pick-ups and drop-offs. In the data set for June 2018, it uses geographic zones rather than longitude and latitude for locations where pick-ups and drop-offs happen. Figure 6 is downloaded from the NYC Taxi data website and it shows the zones created for Manhattan area. We group the small zones in Figure 6 into 12 larger zones (Table 1) and create a bi-directional graph for them. The distance between each zone's center to its neighbor's center is about 2 miles and the travel time estimated by using Google Map is about 10 minutes under a normal traffic condition. The numbers of pick-ups and drop-offs of each zone, with their timing information, are extracted from the data set which are used to calculate distributions of passenger service demands in different time slots.

The distributions are also used to create the pheromone trails used in the ant-based approach.

Artificial vehicles and passengers are created to simulate the system. At the beginning, the vacant vehicles are distributed randomly in different zones. We use a period of 10 minutes as one time slot. The passengers are generated and placed in the zones based on the pick-up distributions for that time slot. When an artificial passenger is generated, a destination of the passenger is also generated based on the drop-off probability distribution. A passenger is matched with a vacant vehicle if they are in the same zone and the vehicle's destination is set as the passenger's destination. The estimated travel time is calculated based on a creation of the shortest path tree of the graph. The occupied vehicle becomes available in the destination zone after the estimated travel time lasts.

Three different design approaches of distributing the vacant vehicles are implemented and compared: local roaming, random walk [Shalamov et al., 2019] and the ant-based approach. In the local roaming approach, once a vehicle becomes vacant, it will stay in the same zone and wait for the next passenger.

In the random walk approach, a vacant vehicle will be either staying in the same zone or distributed to any neighbor zone. The random walk approach uses a uniform probability distribution to move the vehicles and hence the chance for each moving option is the same. In the ant-based approach, how a vacant vehicle moves is based on the probability defined in the formula (1).

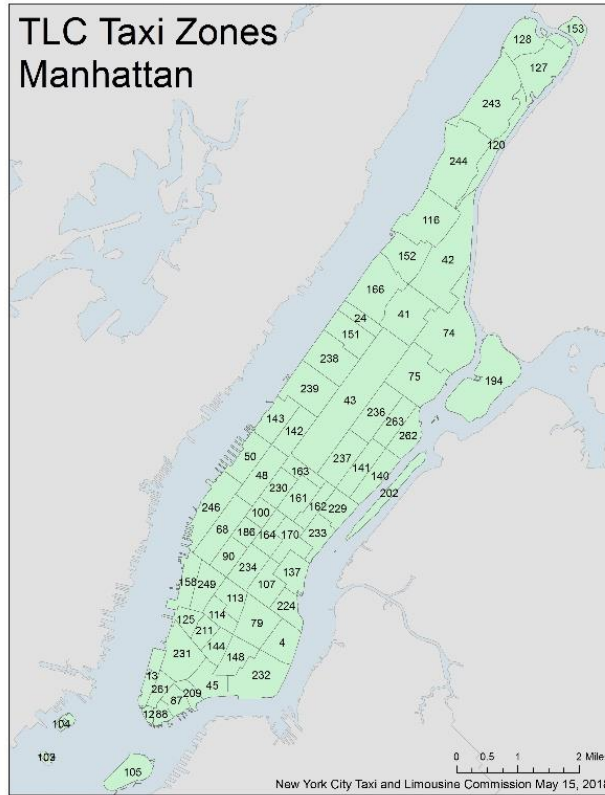


Figure 6. Zones in Manhattan (created by NYC)

Grouped Zone	TLC Taxi Zones Manhattan
1	12, 13, 45, 87, 88, 209, 231, 261
2	4, 79, 148, 232
3	113, 114, 125, 144, 158, 211, 249
4	107, 137, 224, 234, 164, 170, 233, 229, 162, 161
5	90, 186, 100, 230, 163, 68, 48, 246, 50
6	140, 141, 237, 236, 263, 262
7	43, 142, 143, 239, 24, 151, 238
8	74, 75
9	41, 166
10	42, 116, 152
11	120, 243, 244
12	127, 128, 153

Table 1. Grouped Zones Used in Simulations

Experimental Results

The waiting time of each passenger for a pick-up is evaluated in our experiments. In reality, passengers usually do not have patience to wait too long. If the waiting time is too long, they may switch to use some other transportation methods. In the simulations, an upper bound of waiting time is set and each artificial passenger's waiting time is monitored. If a passenger waits longer than the limit, it will assume that the passenger gives up using the service. The numbers of passengers who give up using the service are recorded for the three approaches, respectively. We are also interested in a total vacant time of vehicles which is calculated by the total of time when the vehicles are roaming without any passenger. From a view point of business profits, it is desirable to minimize the vehicles' total vacant time.

The artificial passengers are generated by using data of 4 hours in a day from the NYC Taxi data set. There are 19,896 passengers generated. Figure 7 shows a comparison of average passengers' waiting time among the three approaches based on numbers of vehicles, assuming that the maximum waiting time limit of a passenger is 45 minutes. It can be seen that the ant-based approach achieves the best performance in all cases. Of the other two approaches, the random walk approach is better than the local roaming approach. Figure 8 and Figure 9 show the numbers of passengers who do not get a service because their waiting times are longer than the maximum limit (45 minutes and 30 minutes, respectively). In the simulations, the ant-based approach is the best one. By using it the vehicles serve the most passengers. The results also show that when the ant-based approach is used, 3,500 vehicles is a good number of vehicles to be used in the service areas in terms of the number of passengers in that time slot. Figure 10 shows the total vacant time of the vehicles by using the three different approaches. Along with an increase of the number of the vehicles, the total vacant time increases. The ant-based approach has the smallest total vacant time of each vehicle.

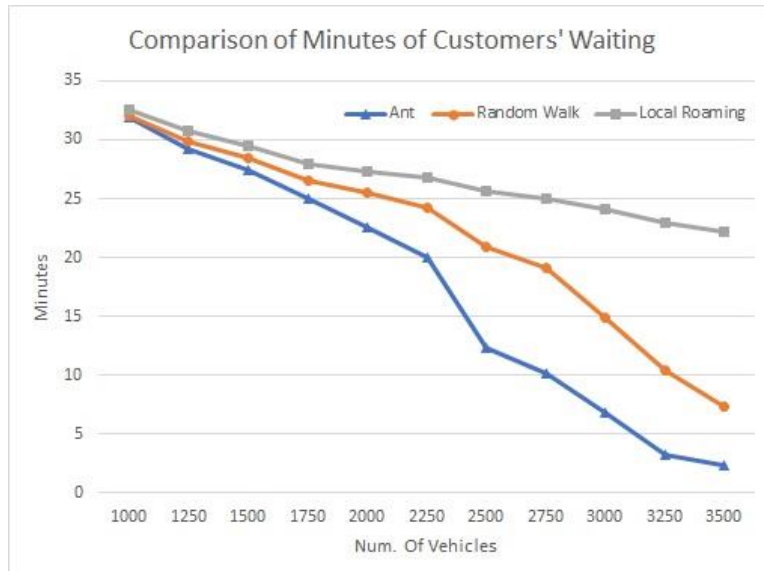


Figure 7. Comparison of Passengers' Waiting Time (max waiting-time limit = 45 mins)

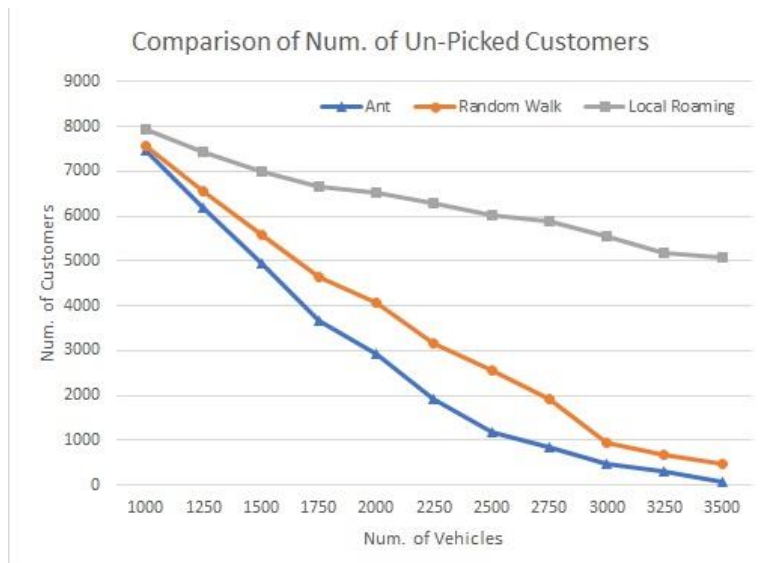


Figure 8. Comparison of Numbers of Passengers Not Getting a Car (max waiting-time limit = 30 mins)

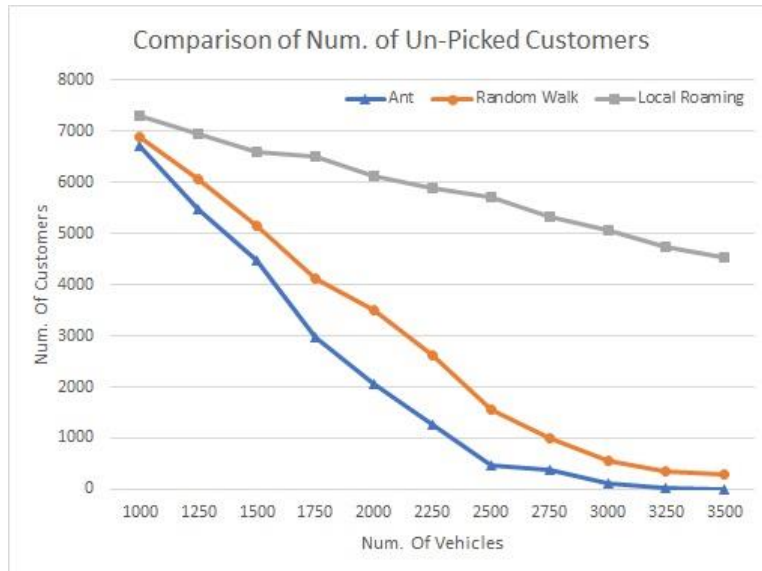


Figure 9. Comparison of Numbers of Passengers Not Getting a Car (max waiting-time limit = 45 mins)

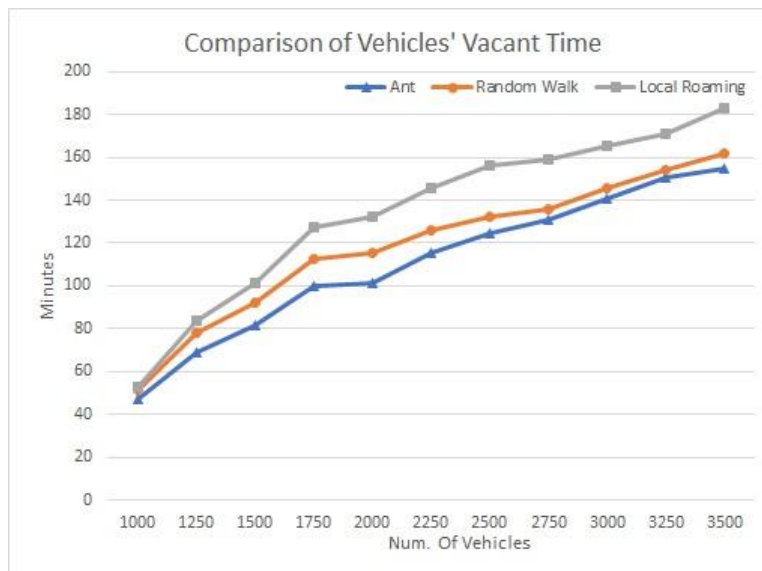


Figure 10. Comparison of Vehicles' Vacant Time (max waiting-time limit = 45 mins)

In addition to the average of passengers' waiting time, Figure 11 and Figure 12 show a distribution of passengers' waiting time with 2,000 vehicles and 3,000 vehicles, respectively. In the figures, there are 9 groups of time in minutes which indicate how many passengers wait at least with those minutes. When 2,000 vehicles are used with the ant-based approach, more than 3,000 of the 19,896 artificial passengers wait at least 10 minutes and about 1,500 passengers wait at least 50 minutes. However, when 3,000 vehicles are used, the number of passengers in each group decreases dramatically. In all groups, the ant-based approach outperforms the other two approaches.

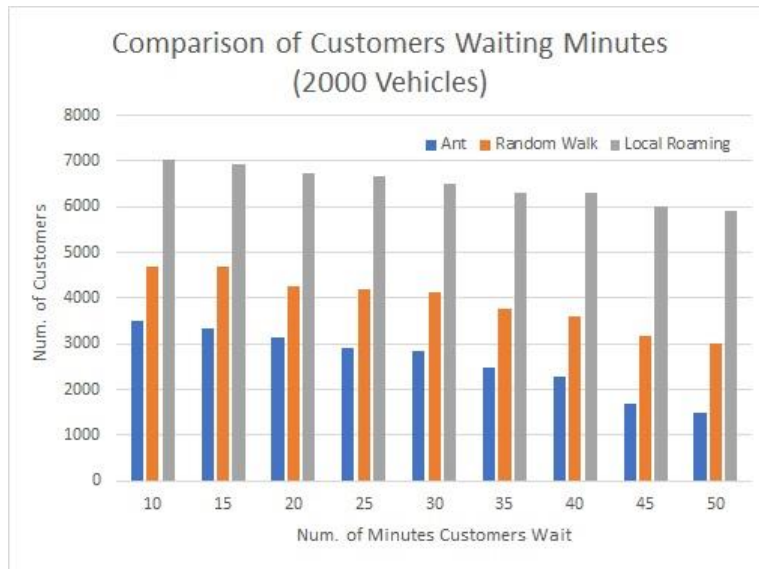


Figure 11. Distributions of Passengers' Waiting Time (2000 Vehicles)

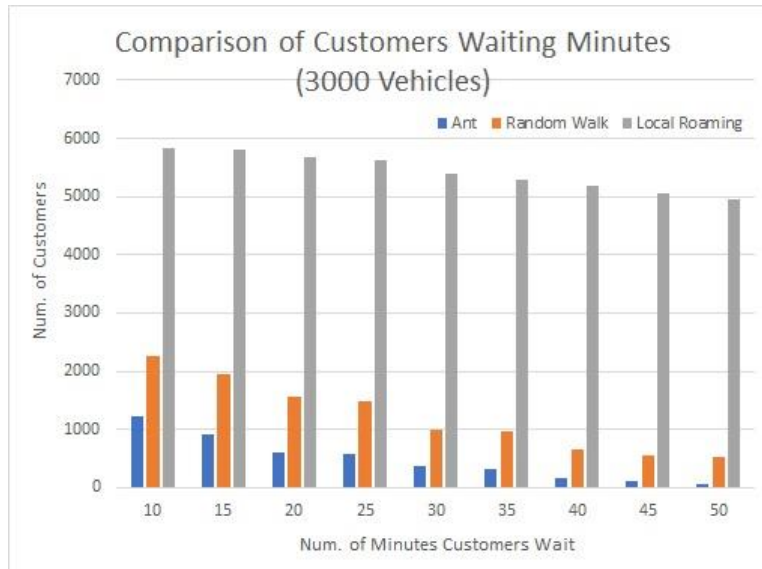


Figure 12. Distributions of Passengers' Waiting Time (3000 Vehicles)

SUMMARY AND FUTURE WORKS

In this paper, we propose a new problem of placing vacant, commercial-service vehicles for the incoming self-driving era. We discuss the reasons why the existing approaches for routing optimization are not suitable for self-driving vehicles and the importance of a new strategy to both passengers and businesses. A novel, stochastic design based on historical data and real-time demands is shown. The experiments demonstrate that our solution is promising to efficiently distribute vacant vehicles to satisfy both passengers' and businesses' needs. We believe that this work is not a finish line of the new problem. In the future we will work on exploring new solutions for the problem, such as including factors of pricing information and priority of service into the considerations.

REFERENCES

- Gehrig, S. K. and Stein, F. (1999). Dead reckoning and cartography using stereo vision for an autonomous car. Proceedings 1999 IEEE/RSJ International Conference on Intelligent Robots and Systems.
- Pomerleau, D. A. (1992). Neural Network Perception for Mobile Robot Guidance, PhD Thesis, Carnegie Mellon University. Waymo. <https://waymo.com/>
- Qian, S., Cao, J. and Mouel, F. L. (2015). SCRAM: A Sharing Considered Route Assignment Mechanism for Fair Taxi Route Recommendations. Proceedings of the 21st ACM SIGKDD Conference on Knowledge Discovery and Data Mining.
- Yuan, J., Zheng, Y., Zhang, L., Xie, X. and Sun, G. (2011). Where to find my next passenger, Proceedings of the 13th international conference on Ubiquitous computing, 2011.
- Qu, M., Zhu, H., Liu, J., Liu, G. and Xiong, H. (2014). A Cost-Effective Recommender System for Taxi Drivers. Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining.
- Zhang, D., Sun, L., Li, B., Chen, C., Pan, G., Li, S. and Wu, Z. (2015). Understanding Taxi Service Strategies from Taxi GPS Traces, IEEE Transactions on Intelligent Transportation Systems, Vol. 16, Issue. 1.
- Alves, D., Van Ast, J., Cong, Z., De Schutter, B., and Babuška, R. (2010). Ant colony optimization for traffic dispersion routing. Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems.
- Lin, Q., Deng, L., Sun, J. and Chen, M. (2018). Optimal Demand-Aware Ride-Sharing Routing, Proceedings of IEEE International Conference on Computer Communications (INFOCOM).
- Adomavicius, G. and Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, Vol. 17, Issue 6.

- Ding, Y., Liu, S., Pu, J. and Ni, L. M (2013). Hunts: A trajectory recommendation system for effective and efficient hunting of taxi passengers. Proceedings of IEEE International Conference on Mobile Data Management.
- Ge, Y., Xiong, H., Tuzhilin, A., Xiao, K., Gruteser, M. and Pazzani, M. (2010). An energy-efficient mobile recommender system. Proceeding of Y. Ge, H. Xiong, A. Tuzhilin, K. Xiao, M. Gruteser, and M. Pazzani. An energy-efficient mobile recommender system. Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining.
- Hu, H., Wu, Z., Mao, B., Zhuang, Y., Cao, J. and Pan, J. (2012). Pick-up tree based route recommendation from taxi trajectories. Web-Age Information Management, Springer.
- Lee, J., Shin, I. and Park, G. L. (2008). Analysis of the passenger pick-up pattern for taxi location recommendation. Proceedings of IEEE the Fourth International Conference on Networked Computing and Advanced Information Management.
- Qian, S., Zhu, Y. and Li, M. (2012). Smart recommendation by mining large-scale gps traces. Proceedings of IEEE Wireless Communications and Networking Conference.
- Wei, L. Y., Zheng, Y. and Peng, W. C. (2012). Constructing popular routes from uncertain trajectories. Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining.
- Yuan, J., Zheng, Y., Zhang, C., Xie, W., Xie, X., Sun, G. and Huang, Y. (2010). T-drive: driving directions based on taxi trajectories. Proceedings of the ACM 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems.
- Yuan, J., Zheng, Y., Zhang, L. and Xie, X. (2013). T-finder: A recommender system for finding passengers and vacant taxis. IEEE Transactions on Knowledge and Data Engineering, Vol. 25, Issue 10.
- Zhang, D., He, T., Liu, Y. and Stankovic, J. A. (2013). Callcab: A united recommendation system for carpooling and regular taxicab services. Proceedings of IEEE International Conference on Big Data.

- Zhang, M., Liu, J., Liu, Y., Hu, Z. and Yi, L. (2012). Recommending pick-up points for taxi-drivers based on spatio-temporal clustering. Proceedings of the IEEE Second International Conference on Cloud and Green Computing.
- Yu, X., Gap, S., Hu, X. and Park, H. (2019). A Markov Decision Process Approach to Vacant Taxi Routing with E-hailing. Transportation Research Part B Methodological, Vol. 121.
- Wardrop, J. G. (1952). Some theoretical aspects of road traffic research. Proceedings of Institute of Civil Engineers.
- Shalamov, V., Filchenkov, A. and Shalyto, A. (2019). Heuristic and metaheuristic solutions of pickup and delivery problem for self-driving taxi routing. Evolving Systems, Vol. 10, Issue 1.
- Grau, J. M. S. and Romeu, M. A. E. (2015). Agent Based Modelling for Simulating Taxi Services. Procedia Computer Science, Volume 52.
- NYC Taxi and Limousine Commission - TLC Trip Record Data. <https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page>.