Demystifying the Crowd Intelligence in Last Mile Parcel Delivery for Smart Cities

Fangxin Wang, Feng Wang, Xiaoqiang Ma, and Jiangchuan Liu

Abstract

Recent years have witnessed an explosive growth of online shopping, which has posted unprecedented pressure on the logistics industry, especially the last mile parcel delivery. Existing solutions mostly rely on dedicated couriers, which suffer from high cost and low elasticity when dealing with a massive amount of local addresses. Advances in the Internet of Things, however, have enabled vehicle information to be readily accessible anytime anywhere, forming an Internet of Vehicles (IoV), which further enables intelligent vehicle scheduling and management. New opportunities therefore arise toward efficient and elastic last mile delivery for smart cities. In this article, we seek novel solutions to improve the last mile parcel delivery with crowd intelligence. We first review the existing and emerging solutions for last mile parcel delivery. We then discuss the advances of the ride-sharing-based delivery mechanism, identifying the unique opportunities and challenges therein. We further present *Car4Pac*, an IoV-enabled intelligent ride-sharing-based delivery system for smart cities, and demonstrate its superiority with real trace-driven evaluations.

Introduction

During the past decade, online shopping has dramatically changed people's lifestyles. Its explosive growth heavily relies on the underlying support of the logistics and transportation industries. In the whole logistics chain, the citywide *last mile parcel delivery* (namely, from distribution centers or substations to individual addresses) is often the bottleneck and the most expensive segment, consuming 13 percent to even 75 percent of the entire delivery cost [1]. Also, the last mile parcel delivery can occupy a copious amount of transportation resources, which can exacerbate urban environment pollution and traffic congestion.

The key problem lies in the mismatch between the limited delivery efficiency and the ever increasing parcel delivery demand. Traditional logistics providers usually maintain dedicated couriers, while the fixed delivery capacity can fail to catch the varying delivery demand. During popular online shopping festivals, they can hardly meet the promised delivery deadlines due to the sudden boost in parcel amount. The uncertain delivery time causes a high missing reception rate, which seriously undermines the quality of experience for online shopping [2]. Some service providers (e.g., Amazon Flex[1]) try to leverage part-time couriers for last mile delivery to improve cost effectiveness and elasticity. However, this approach is still far from cost-efficient, and the corresponding delivery traffic also contributes to citywide pollution and traffic congestion.

In recent years, unmanned-vehicle-based solutions are also emerging for last mile parcel delivery. While they can significantly reduce or even eliminate the expensive manpower cost, they are mostly explored as individual entities; for example, existing unmanned carriers are only experimented on in very specific environments with point-to-point delivery. There is still a long way to go to deploy them in scale and explore their collective capabilities in the complex real environment to achieve a *smart city*.

In fact, the hidden delivery capability within an urban environment is enormous, not to mention that with unmanned vehicles. As one of the most promising networking paradigms, the Internet of Things (IoT) bridges the gap between the cyber world and the physical world, enabling the pervasive end devices to achieve collaborative sensing, processing, and computing [5]. In particular, the citywide vehicle resources can be connected and associated together as an intelligent transportation system through the well-established networks (e.g., fourth/fifth generation, 4G/5G [6], and vehicular networks [7]) for many applications (e.g., navigation [8]), which is referred to as the Internet of Vehicles (IoV). Our analysis on real vehicle trajectories in several major cities has shown strong evidence that everyday car trips are rich enough to cover every area in these cities. This opens the opportunity toward a new generation of last mile delivery that explores crowd intelligence. In particular, citywide car trips are a rich set of resources to share, with parcels being hitchhiked, as illustrated in Fig. 1.

In this article, we first provide an overview of the present and emerging solutions for last mile parcel delivery. We then demystify the advances of IoV-enabled crowd intelligence in parcel delivery, examining the unique opportunities and challenges therein. We further present *Car4Pac* [9], a novel last mile parcel delivery system for smart cities through intelligent car trip sharing. Our real trace-driven evaluations demonstrate the superiority of Car4Pac, which can accurately predict the extra delivery cost with only about 15 percent error ratio and complete up to 25 percent more delivery tasks than the baseline approaches. To the best of our knowledge, Car4Pac is the first to

[1] https://flex.a mazon.com/

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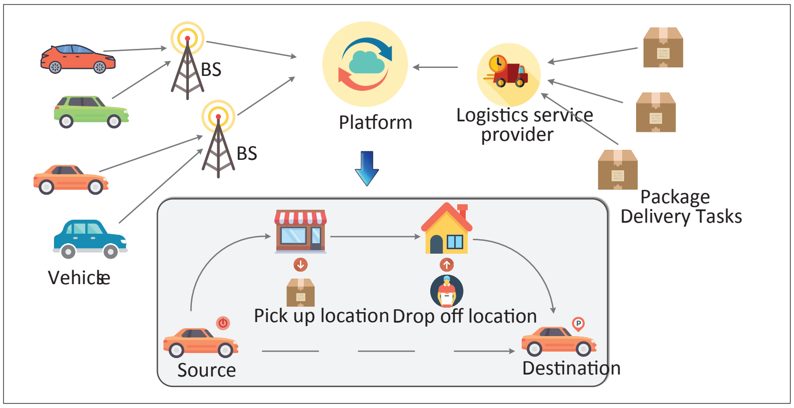

FIGURE 1. The architecture of IoV-enabled ride-sharing-based last mile parcel delivery. A driver is planning to travel from the source to the destination through the dashed route. Assume that a parcel is scheduled to be delivered from a shop to a house, where the shop is close to the source and the house is close to the destination. Then the driver can deliver this parcel incidentally during the trip through the alternate route shown by the solid line.

explore the opportunities of having parcels hitchhiking private car trips with accurate cost prediction and effective delivery task assignment, which not only achieves time-precise delivery and cost efficiency, but also reduces traffic congestion and carbon emission.

Last Mile Parcel Delivery: Present and Emerging Solutions

Last Mile Parcel Delivery: The Present

Traditional logistics service providers (e.g., Canada Post[2]) mostly rely on dedicated couriers and vehicles for parcel delivery. However, there are also some key problems associated with last mile parcel delivery.

First, it is difficult to achieve time-precise delivery. Users always prefer more convenient and secure delivery service [2] such as home delivery with a signature of reception rather than dropping off parcels at the door. If no specific time window is allowed, the missing reception rate can be high since recipients are not likely to wait at home all day. A hard pre-arranged short delivery window specified by users can guarantee one-time successful delivery. But such restrictions will inevitably compromise the delivery efficiency because the carrier may have to come to similar locations during different pre-arranged time windows, and the delivery route will become more back and forth.

Second, the lack of elasticity is also a crucial issue. Large online shopping festivals (e.g., Black Friday in the United States) usually see a very high amount of parcels for delivery within a short time period. When the promotion period ends, the delivery demand quickly drops to the normal level or even much lower than average. Maintaining dedicated couriers is inflexible to keep pace with the fluctuation of delivery demand.

Furthermore, the delivery cost efficiency heavily relies on the density of delivery addresses [10]. Without adequate market density and penetration, the delivery addresses can be quite sparse, so a courier is likely to drive tens of miles for just a single parcel delivery. Such circumstances further reduce the cost efficiency and lead to a high average delivery cost.

Some service providers (e.g., Amazon Flex) try to hire part-time couriers for parcel delivery. Compared to employing dedicated couriers, the improvements lie in the ability to flexibly adjust the transport capacity to accommodate the ever changing delivery demand and the reduction of the infrastructure maintenance cost. While largely improving the elasticity, this approach still cannot guarantee highly time-precise delivery since the drivers will not promise to deliver parcels exactly during a short time slot.

Unmanned Delivery with IoT: Emerging Solutions

In order to combat the existing problems, a series of new unmanned delivery approaches for last mile delivery have emerged. We elaborate on them as follows.

Autonomous vehicles. In recent years, autonomous vehicles (AVs) have seen great potential in bridging the last mile in open outdoor environments due to the fast development of self-driving and smart vehicle-related technologies [3]. DHL[3] began testing self-driving trucks in the second half of 2018. Yu *et al.* [4] proposed a novel AV logistics system and focused on determining the optimal routes for the governed AVs. The advantages of AVs lie in many aspects, such as increasing delivery efficiency and liberating human forces. However, current unmanned driving technology is still far from mature, which largely limits its wide deployment.

Unmanned aerial vehicles. Unmanned aerial vehicles (UAVs) or drones are promising in relieving congestion in urban areas and improving accessibility in rural areas, moving the delivery off the road and into the air. The industry is actively trying parcel delivery using UAVs (e.g., Amazon's PrimeAir[4] and Google's Wing[5]), aiming to deliver parcels within a very short time period. Despite its high efficiency and convenience, UAVs also face severe challenges (e.g., restricted applicable regions, limited coverage, and high device costs), which remain to be solved in the future.

Intelligent robots. As a lightweight carrier, intelligent robots are also applied well in the logistics field, especially in particular delivery environments, such as well controlled communities and complicated indoor environments. China's B2C e-commerce giant JD[6] has planned to replace humans with intelligent robots for on-campus parcel delivery. Even with great convenience and advances in particular environments, intelligent robots are usually used as secondary delivery carriers given the limited capacity and delivery coverage.

These aforementioned emerging delivery approaches reveal their respective potentials in improving last mile parcel delivery. They either seek a more advanced driver-based approach or embrace the rising unmanned driving technologies to achieve high individual intelligence, namely, making each individual vehicle more intelligent for delivery. Even so, they are still insufficient to make an all-around solution to achieve time-precise, elastic, and cost-efficient delivery with large coverage, as illustrated in Table 1. The citywide collective capacities of vehicle resources are still far from being explored.

[2] https://www.canadapost.ca/

[3] http://money.cnn.com/2017/10/11/technology/future/dhl-autonomous-delivery-truck/index.html

[4] http://www:amazon.com/primeair

[5] https://x.company/wing/

[6] http://www.chinadaily.com.cn/business/tech/2017-11/07/content_34228952.htm

Approaches	Categories	Researches and Solutions	Time-precision	Elasticity	Cost Efficiency	Coverage
Dedicated couriers	Driver based delivery	Canada Post[2]	Low	Low	Low	Large
Part-time couriers	Driver based delivery	Amazon Flex[1]	Medium	High	Medium	Large
Autonomous vehicles	Unmanned delivery	DHL,[3] Lam *et al.* [3], Yu *et al.* [4]	Low	Low	Medium	Medium
Unmanned aerial vehicle	Unmanned delivery	PrimeAir,[4] Google Wing[5]	Low	Medium	Medium	Medium
Intelligent robot	Unmanned delivery	JD on-campus robot[6]	Low	Low	Medium	Small

TABLE 1. A summary of present and emerging solutions for last mile parcel delivery.

Ride-Sharing-Based Delivery: From Individual Intelligence to Crowd Intelligence

IoV connects citywide vehicles toward an intelligent transportation system. The crowd intelligence therein has great potential to explore beyond those from individual entities; in particular, it casts light on ride-sharing-based delivery, which fully integrates the ubiquitous citywide transportation resources with the massive parcel delivery demands. The basic idea is sharing existing car trips to incidentally deliver parcels with a proper reward.

The foundation of ride-sharing-based crowd delivery relies on the rich car trip resources in a citywide range. To verify this, we collaborate with Mojio,[7] a leading open platform for connected vehicles, and collect a dataset of car trajectories and driving records in three cities (i.e., Vancouver, Houston, and Miami) from 9 June to 30 June 2016. This dataset includes more than 12 million data entries of 1275 vehicles, recording the timestamp, GPS information, remaining fuel level, and so on. We examine the citywide car trip trajectory coverage and find that the car trip trajectories cover almost all areas of these cities, indicating abundant car trip resources for ride-sharing-based delivery.

Ride-sharing-based crowd delivery reveals many unique advantages. From the drivers' perspective, the additional parcel delivery tasks exert only marginal impacts on the driver since the drive routes with and without parcel delivery tasks do not change much. But the task completion rewards can be very attractive, compensating the cost of the trip. From the service provider's perspective, the sharing-based approach is highly flexible and thus has great potential for elastic and time-precise deliveries. The cost is also lower than sending dedicated couriers for parcel delivery. From the city's perspective, ridesharing can effectively reduce traffic congestion and carbon emissions, increasing the transportation resource utilization. Therefore, ride-sharing-based last mile parcel delivery is a trilateral win-win solution for all parties.

Although desirable, it is still challenging to turn this idea into a practical system. We next discuss the main challenges therein from a research perspective as follows.

Travel time estimation. An accurate travel time estimation is a prerequisite for time-precise parcel delivery. Different from hiring specialized couriers with well-controlled delivery, ride-sharing-based delivery relies on various car trips, which have huge diversities in delivery time due to time-varying traffic conditions, drivers' different driving behaviors, and so on. Hence, how to achieve accurate delivery time estimation for diverse car trips remains a research challenge.

Delivery task assignment. Given a particular delivery task, there may be many feasible assignments. Different car trips can have different extra costs (e.g., extra time and fuel) when performing the same delivery task. How to conduct an optimized assignment is challenging, especially when there are large amounts of car trips and delivery tasks, and each car trip is allowed to take multiple delivery tasks.

Incentive mechanism design. Drivers will not deliver parcels for free, which means that an attractive incentive (e.g., a monetary reward) needs to be offered for the delivery tasks. Designing a proper incentive mechanism is a crucial problem for service providers. Furthermore, delivery tasks with diverse destination addresses can require different rewards, making this problem even more challenging.

Car4Pac: A Case of Crowd Delivery

We propose *Car4Pac*, a novel citywide parcel delivery system to demonstrate how ride-sharing-based crowd delivery can be implemented. We assume that a driver is willing to take parcel delivery tasks as long as the incentive rewards are higher than the extra time and fuel cost for taking the tasks. The framework of Car4Pac consists of three components, namely, triple-dependent travel cost analysis, trip cost estimation, and delivery task assignment, as illustrated in Fig. 2.

Triple-Dependent Landmark Graph Construction

We start by constructing a routable graph called a landmark graph from the collected massive historical car trip trajectories to represent the complex citywide road network. When two trajectories intersect, we identify the point of intersection as a landmark, indicating a vertex in our graph. We first consider calculating the weight (i.e., the time and fuel cost) for each edge. With the GPS points, timestamps, fuel level, and so on, we can easily get all the time cost and fuel consumption for each car trip that goes through a particular edge.

The time and fuel costs of traversing an edge highly depend on the traffic conditions, which are closely related to different departure times. A typical example is that in rush hours, traffic is more crowded than at other times, leading to more fuel consumption and longer travel time on the same road. Car4Pac adopts a fine-grained two-level method to accurately capture the time-dependent features of travel time cost and fuel cost on each edge. The first level is day-level partition, which divides a workday into rush hours W_r, daytime

[7] https://www.moj.io/

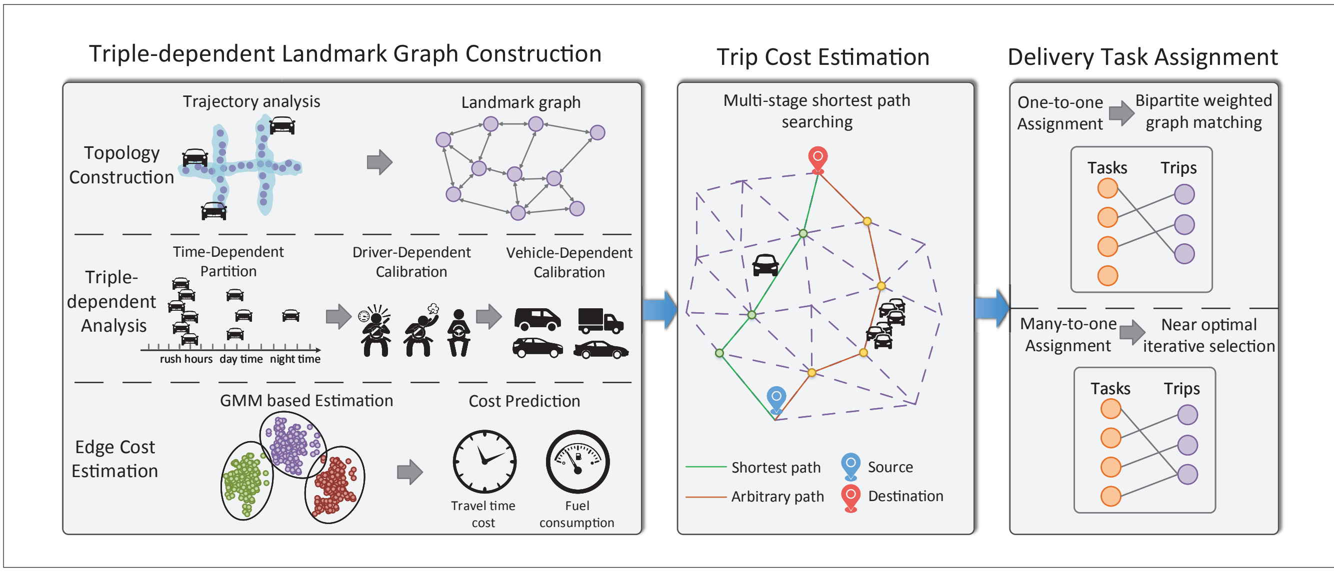

FIGURE 2. The Car4Pac framework of IoV enabled last mile parcel delivery for smart cities.

hours W_d, nighttime hours W_n, and divides the rest of the day into daytime R_d and nighttime R_n. The second level is the minute level, dividing a day into

$$L = \left[\frac{24 * 60}{\alpha} \right]$$

time slots, where α indicates the interval minutes between the beginning of two consecutive slots (e.g., 15 minutes).

Besides the time-dependent traffic conditions, people's different driving skills also impose an obvious impact on the cost of travel time for a particular edge (e.g., skilled drivers tend to drive faster than learners). We define the *Driving Skill Index* DS_u of a driver u as the mean ratio between his/her travel time through every road and all drivers' average travel time through the same road. Through examining all the trip records in our dataset, we identify different drivers of each trip and calculate their individual driving skill index accordingly. We then calibrate the travel time cost for a road at a given time period by dividing each cost by the corresponding DS_u. Similarly, car trips with different vehicle types usually have different fuel efficiency, causing diverse fuel consumptions. We define the *Fuel Efficiency Index* FE_v of a particular vehicle type v as the ratio between its fuel efficiency and the baseline fuel efficiency of a given benchmark vehicle type. We then calibrate the fuel consumption cost by dividing each cost by the corresponding FE_v.

We consider the costs of each edge in each time slot as random variables and learn them via the Gaussian mixture model (GMM) due to two reasons. First, it is able to approximate any complex probability distributions, which outperforms other simple methods such as exponential distribution functions. Second, GMM achieves relatively good performance given the limited data support, while other advanced prediction methods such as long short-term memory (LSTM) only yield good performance with massive and fine-grained data. The expectations of corresponding random variables are then calculated as the estimated benchmark cost.

Trip Cost Estimation

We next consider how to select the optimal routing path for a particular trip and achieve a personalized trip cost estimation. Different from the traditional static shortest path problem, the travel time and the corresponding cost of each path are uncertain given that the cost of each edge in the landmark graph is time-dependent, driver-dependent, and vehicle-dependent. Thus this problem is actually finding the shortest path in a dynamic weighted graph, where we consider finding an optimal path to minimize the travel time for a given trip.

The problem can be divided into two situations. First, if a travel trip is very short and the entire time period falls in one time slot, we can simply use a traditional shortest path finding algorithm such as Dijkstra's algorithm [11] to find the travel path with the least travel time cost since the graph is actually static in this situation. Second, if a trip will travel through several time slots, we extend the algorithm to solve this dynamic shortest path problem in multiple stages, where a stage corresponds to one time slot, and we begin the path search in the next stage based on the temporary results of the previous stage. After obtaining the benchmark cost values, we then re-calibrate each personalized cost via multiplying the benchmark cost by the corresponding driving skill index and fuel efficiency index.

Delivery Task Assignment

The objective of this component is to assign delivery tasks to the most appropriate car trips so that the social welfare can be maximized. This problem is actually equivalent to finding the optimal task-trip matching so that the total time and fuel cost is minimized.

A successful task-trip matching must satisfy two basic requirements. First, the assigned parcel must be delivered precisely within the given time window. Second, since different drivers may have different extra cost to take the same parcel, the reward for task completion should be higher than the extra cost of the assigned driver (i.e., the utility of that driver must be positive). We filter out

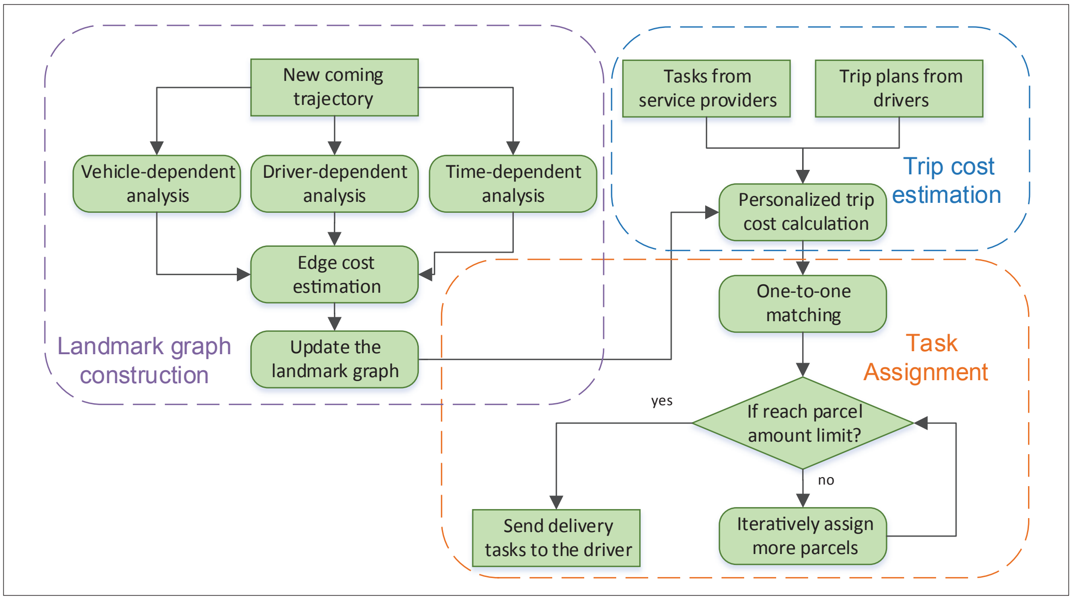

FIGURE 3. The system workflow of Car4Pac.

unqualified trips for each delivery task based on the two requirements, and then develop a two-stage algorithm toward the parcel delivery task assignment, namely, one-to-one matching and many-to-one matching.

In one-to-one matching, we allow each car trip to take at most one parcel. Given the certain calculated trip routes in the routing graph, the arrival time of a parcel and the extra cost of this trip can be determined. In this way, this task assignment problem can be abstracted as a weighted matching problem in a bipartite graph. We next convert the graph into a balanced completed bipartite graph by adding dummy nodes and virtual edges with zero weight. Then we can solve the *minimum weighted bipartite perfect matching* by the Hungarian algorithm [12] and further obtain the task allocation results.

In many-to-one matching, a car trip can take multiple parcels (within a limitation) for delivery, which further increases the transportation resource utilization. However, this many-to-one optimization problem is NP-complete since the extra cost of taking one more parcel is not linearly additive, and the search space grows exponentially with the number of parcels a driver is allowed to take. We propose a car-trip-aware heuristic algorithm based on the one-to-one assignment result to address this problem in an iterative way. In particular, in each iteration, we select an available assignment with the largest utility gain and update the new trip routes. We repeat this process until no task can be assigned anymore. The system workflow of Car4Pac is illustrated in Fig. 3

Evaluation

We have conducted extensive real-world trace-driven experiments to study the performance of Car4Pac, particularly with Mojio's car trip data in the city of Vancouver with more than 12 million data records. We split the entire dataset into a training set and a testing set for the personalized trip cost estimation. We empirically generate parcel delivery task data for evaluation as follows. The delivery time window is randomly generated from 9 a.m. to 7 p.m. considering the practical situation. Also, the source and destination locations for each task are randomly specified with an equal probability.

We start from examining the average prediction error ratio of travel time (ERT) and fuel consumption (ERF). Figures 4a and 4b illustrate the impact of different time slot granularities on the prediction error ratio. We can find that when the time slot setting is $\alpha = 15$ minutes, the error ratio of time cost and fuel consumption are minimal compared to other settings. This is because when $\alpha = 5$, the time slot interval is so small that many roads lack enough data records, making the travel time cost calibration less effective. On the other hand, if we set $\alpha = 30$ or $\alpha = 60$, the road conditions during a time slot can vary a lot due to the coarse-grained time slot partition, also leading to a larger error ratio. Therefore, we choose $\alpha = 15$ as the default setting for our experiments.

Figures 4c and 4d further investigate how the calibration of driving skill index and fuel efficiency index would affect the prediction errors of both travel time and fuel cost. It is clear that with both calibrations, the error ratios are remarkably lower than those without such calibrations, with an average of about 20 percent error ratio reduction. This result demonstrates the effectiveness of our personalized estimation that considers the diversity in driving behaviors and vehicle fuel efficiencies.

To better evaluate the performance of our task delivery algorithm, we implement two baseline methods for comparison, namely, Closest Deadline First (CDF) and Shortest Distance First (SDF). For CDF, each time we consider the task with the closest deadline and assign it to the first available trip with the earliest departure time. For SDF, we prefer selecting the task-trip match with the shortest extra driving distance rather than considering the maximum utility. Figure 5a shows the impact of different lengths of user-specified delivery window on the task completion rate. We can observe that as the delivery window becomes relaxed, the task completion rate increases accordingly for

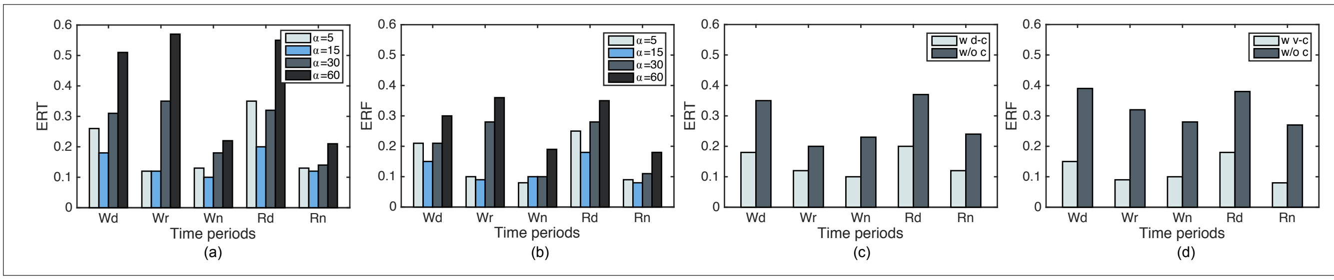

FIGURE 4. The evaluations on the prediction of travel time cost and fuel consumption: a) error ratio of travel time with various time slot settings; b) error ratio of fuel consumption with various time slot settings; c) error ratio of travel time with driver-dependent calibration and without this calibration; d) error ratio of fuel consumption with vehicle-dependent calibration and without this calibration.

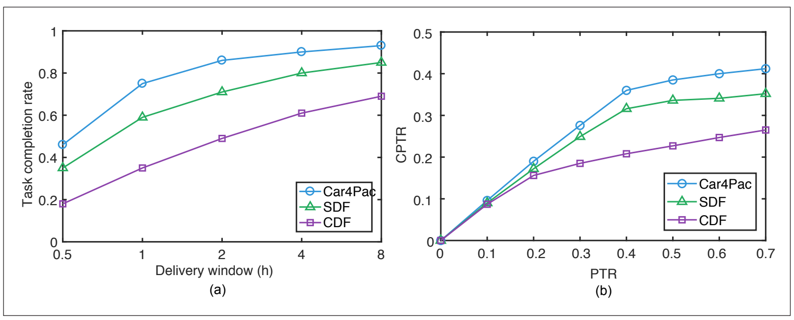

FIGURE 5. Evaluation on delivery task assignment: a) evaluation of task completion rate under different user-specified delivery time windows; b) the value of CPTR when setting different PTR.

every method. For a typical delivery window of 2 hours, Car4Pac remarkably outperforms SDF and CDF by 21 and 75 percent, respectively, indicating that Car4Pac is more capable of achieving time-precise delivery.

Figure 5b shows the ratio of completed parcels to trips (CPTR) when generating tasks by different ratios of parcels to trips (PTR). We can find that when PTR is small (e.g., less than 0.2), most tasks can be completed as the ratio of CPTR to PTR is close to 1. As the PTR increases and reaches 0.4, the CPTR begins to increase very slowly, which indicates that the tasks have already exceeded the delivery capacity of car trips. On the other hand, the CPTR of Car4Pac is 10 percent higher than that of SDF and achieves about 25 percent higher than that of CDF. This result shows Car4Pac is more capable of handling the massive delivery tasks effectively.

In the practical deployment, Car4Pac only needs to update edge cost once every time slot, and the delivery task assignment is an offline process with polynomial complexity. Thus, Car4Pac is able to achieve real-time processing.

Further Discussion

Ride-sharing-based parcel delivery has attracted research in recent years due to its unique advantages nowadays. Existing research studies such as Crowdphysics [13] and Crowddeliver [14] mostly focused on exploring the relays of multiple independent deliveries by humans or vehicles until parcels reach the final destination. These mechanisms require close collaborative efforts of many participants and temporary parcel storage, which raises uncertainty in the delivery process and makes it hard to achieve time-precise delivery. In contrast, Car4Pac solves the last mile parcel delivery through IoV-enabled intelligent ride sharing with accurate cost prediction and effective task assignment. Car4Pac is also robust against various stochastic and extreme situations such as no available trips, where dedicated couriers will handle the delivery tasks left.

Ride-sharing-based delivery also faces challenges from the social aspect. Among them, the most significant concern is the privacy issue, given the nature of the open access and resource sharing of connected vehicles [15]. The trip information for each vehicle owner should be well protected against privacy leakage. Beside, given that the parcel "couriers" in the ride sharing context are massive numbers of normal drivers rather than professional delivery people, the security of the parcels and recipients is another key concern in this smart city scenario. Thieves and criminals may pretend to be drivers to steal parcels of high value or even rob recipients. Thus, an effective rating system with real-name certification for drivers is necessary to establish a complete trustworthy system.

In the near future, unmanned delivery approaches can supplement or even replace the ride-sharing-based approaches for the last mile parcel delivery. Compared to ride-sharing-based approaches, unmanned delivery approaches have no pre-defined driving routes, and different vehicles can be applied well in different scenarios so that operators can flexibly schedule the delivery strategy and path. For example, autonomous vehicles can move freely in a city carrying a batch of parcels, and UAVs are used to deliver parcels for the last short distance. Thus, how to collaboratively schedule the unmanned delivery approaches to achieve cost efficiency and fast delivery is also a promising research direction.

Conclusion

In this article, we study the ride-sharing-based last mile parcel delivery in the era of connected and smart vehicles. A review of existing problems in last mile parcel delivery is presented, followed by a discussion of emerging solutions. We then discuss crowd intelligence in ride-sharing-based parcel delivery, identifying the unique opportunities and challenges therein. With a case study of Car4Pac, we further demonstrate the superiority of this ride-sharing-based delivery approach. Given the remarkable potential of crowd intelligence with ride sharing, we believe this is a promising IoV-enabled solution for smart cities toward time-precise, elastic, and cost-efficient last mile parcel delivery.

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Given the remarkable potential of crowd intelligence with ride sharing, we believe this is a promising IoV-enabled solution for smart cities toward time-precise, elastic, and cost-efficient last mile parcel delivery.

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