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RESEARCH ARTICLE

Task bundling effect in electric scooter charging platform

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ABSTRACT
This study proposes two innovative optimization-based bundling algorithms to offer attractive options to the decentralized workforce in the electric scooter-sharing platform. The applicability of bundles is raised in enticing workers to a side hustle system of collecting low-battery scooters for a reward per task. The proposed bundling strategy considers the domain-specific characteristics of the scooter charging industry, such as autonomous task selection of workers, depot-oriented workers, a bundle decision phase before the worker selection phase, and limited information on workers' task preferences. Based on assumptions about worker behavior, the value maximizing bundling (VMB) model aims to generate bundles with a higher reward-to-distance ratio, while the probability maximizing bundling (PMB) model additionally considers the distance required to reach the bundle centroid from the worker depot. The effectiveness of these bundling strategies is evaluated through a series of simulation experiments. Findings suggest that bundles significantly improved scooter collection rates compared to non-bundling scenarios. Additionally, this strategy enhances workers' profit margins. Scenario-based simulations further demonstrate conditions that amplified the impact of bundling on the overall worker capacity and scooter distribution patterns. Given the superior performance of the PMB model with optimal parameters and the consistent stability of the VMB model, the study offers actionable insights for managers considering the implementation of bundling strategies.

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gig economy; shared electric scooter; simulation; spatial crowdsourcing; task bundling

1. Introduction

The popularity of electric scooter-sharing services has been steadily increasing with the emergence of the smart city and shared micro-mobility (Kadri et al., 2015; Lu et al., 2024; Orozco-Fontalvo et al., 2023). Major companies such as Lime, Bird, and Jump offer scooter rental services to customers for short-distance travel (Fang et al., 2015). Dockless scooters provide easy access as they can be reserved *via* an app and dropped off at any location after use. As a sustainable transportation, electric scooter trips have replaced 57% of trips made by foot, bicycle, and skateboard; and 28% of trips made by car, motorcycle, and taxi (Fitt & Curl, 2019). The market size is 925.3 million USD in 2021 with a compound annual growth rate of 18.8% from 2022 to 2028 (Grand View Research, 2020). Easiness of accessibility and user-friendly platform applications are major advantages that support the business.

Meanwhile, the platform suffers from charging the low-battery scooters widespread within the service area (Singgih & Kim, 2020). According to Wilhelm (2018), 47% of the revenue is used back in the charging operation, which needs the most attention to lower the overall cost. Among charging systems to gain a competitive edge, some companies contract with "gig workers." The term "gig" comes from the gig economy, where the platform engages with workers temporarily to perform company work (Lord et al., 2023). In the case of the electric scooter-sharing platform, the platform compensates gig workers for charging low-battery scooters. Major companies provide these side hustle services through uniquely named programs like "Lime Juicers" (https://lime.bike/juicer). The scooter-picking process mainly starts in the evening, around 9 or 10 pm, when scooter riding usage decreases. The location of scooters that need charging is displayed on the app. Workers can reserve one scooter at a time, collect it, and repeat this process until they finish their tasks for the day. They then return home to charge the scooters and complete relocation by the morning deadline. Usually, the charging operation is carried out at the workers' depots using chargers provided by the platform upon registration. After task completion, workers receive payment based on the tasks completed daily. For example, "Lime juicers" typically earn 4–5 dollars per task, but the reward can go up to 12 dollars for hard-to-find scooters (Elkins, 2019). This system is more cost-effective than operating a company-oriented vehicle to visit all scooters by leveraging the distributed network of gig workers. Also, it gains public support and loyalty effect over competitors, by offering side hustle opportunities.

Under this gig system, the platform relies on gig workers to achieve maximum scooter collection rates to guarantee reliable user service the following day. However, this

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expectation poses several considerations for the platform. First, the number of workers varies significantly daily due to open participation and flexible working hours. On days with fewer participants, the collection rate inevitably reduces. Second, gig workers prioritize their profit, often leaving several scooters uncollected. As workers autonomously select only profitable tasks, the collection rate might remain low according to scooter and worker distribution. To attract gig workers, tasks must offer sufficient rewards to cover the travel distance or encourage workers to extend their working hours even after meeting their earnings goal. In this context, the platform requires centralized decision-making to efficiently entice the decentralized workforce to maximize the daily collection rate.

One innovative approach to entice independent workers is bundling tasks to increase worker valuation. Initially developed for freight service procurement, bundling strategies grouped transportation lanes for independent carriers, who bid on desired bundles through combinatorial auctions (Song & Regan, 2003). In a case study by Olivares et al. (2012), a strategic behavior among carriers was observed, where they submitted higher bids for bundles with smaller sizes and higher proximity. This is because tasks within a good bundle have a complementary property by requiring less empty movement or detour for workers, increasing the willingness to engage.

Nowadays, various crowdsourced business sectors, such as crowdsourced delivery and mobile crowdsensing, have adopted task bundling, with methods customized to the specific service characteristics of each field. In this context, a task bundle refers to multiple customer requests or a demand point represented by specific locations. In the field of crowdsourced delivery, bundling strategy is based on worker interaction or an auction system. Approaches based on these additional feedback processes guarantee that bundles created or assigned to workers are sufficiently valuable. In Horner et al. (2021), the platform presents each worker with personalized task options and revises the task assignment based on direct feedback. Meanwhile, the auction system can assign tasks for all workers at once equally, where the quality of a bundle is estimated through the bid price. While Triki (2021) dealt with a system where workers create their own task bundles as bids, Mancini and Gansterer (2022) presented a bundle generation problem for the auctioneer, which is likely to be perceived as valuable by workers. On the other hand, in the mobile crowdsensing sector, where task engagement is simple with a smartphone, the strategy focuses on creating attractive bundles without requiring worker confirmation. To address the uncertainty of worker preferences for bundles, the literature has developed proxy objective functions to enhance worker engagement. Gansterer and Hartl (2018) evaluated the attractiveness of a bundle based on factors such as tour length, density, and isolation of the bundle. Subsequent studies have included additional factors to define the probability of a bundle being selected, such as the bundle size and detour cost relative to the worker's original trajectory (Zhao et al., 2021), or have incorporated task popularity categorization results into the bundle construction process (Wang et al., 2019; Zhen et al., 2022).

Similarly, in the scooter charging industry, offering bundle reservations in addition to individual ones can present more valuable choices that boost worker engagement. Unlike the current one-task-at-a-time reservation system, which may lead to unpredictable work schedules and create anxiety about losing potential tasks to others, bundle reservations offer greater predictability. By securing multiple tasks at once, workers can plan longer working hours and achieve higher earnings, reducing uncertainty. Meanwhile, offering bundle reservations can alleviate some of this uncertainty by ensuring workers have longer working times and higher earnings than individual reservations.

However, the unique characteristics of the scooter-sharing platform call for a specialized bundling algorithm that has not been explored in prior studies. Gig workers are assumed to be depot-oriented rather than trajectory-based, as their shifts typically begin at night from the depot, where they equip their vehicles and prepare for plug-in charging. Additionally, quick task bundling is crucial for worker engagement, making auction-based or feedback-driven methods impractical. Moreover, key information such as travel routes or task preferences is unavailable due to the spontaneous participation of workers, necessitating a new approach based on available information on scooter distribution and depot data.

This study introduces a bundling strategy to entice gig workers to maximize daily scooter collection rates. To the best of our knowledge, we are the first to propose an operational approach to using bundles in the scooter-sharing industry, leveraging gig workers for charging by autonomous task selection. Our approach involves a two-stage bundling strategy. Initially, candidate bundles are generated *via* a bundle generator to reduce the computational load by focusing on potentially attractive combinations of tasks. Subsequently, the final configuration of non-overlapping bundles is selected using a set-packing optimization model, each maximizing a proxy objective to evaluate bundle attractiveness.

The contribution is threefold:

- This study fills the research gap of the task bundling literature applicable to the scooter charging industry to maximize the task completion rate. It targets self-scheduling, depot-oriented gig workers who can make multiple sequential task reservations. Unlike previous studies that rely on auction systems or feedback on bundle quality, the proposed model generates bundles directly before the worker selection phase, without considering task preferences or feedback.
- Two proxy objective functions of the set packing model are designed for assessing the bundle attractiveness. The value maximizing bundling (VMB) model uses task distribution information to maximize the sum of bundle value, defined by the total reward divided by the dispersion of tasks. The probability maximizing bundling (PMB) model maximizes the collection probability by considering the proximity of the bundle to the worker's

depot in addition to its value. Both models are designed using only the minimum available information in the industry.

- Numerical experiments are conducted to demonstrate the effectiveness of bundles with scooter collection simulation. Our approach increases the collection rate near the maximum achievable collection rate calculated under centralized task assignment without bundles in the benchmark comparison. The efficacy of the bundling strategy was further examined across different scenarios, considering the spatial distribution of scooters and the total capacity of workers. By analyzing actual scooter data from Louisville, this study demonstrated that the proposed bundling strategy increases the average profit margin for workers, thereby confirming its benefit for both the platform and gig workers.

The remainder of this article is structured as follows. Section 2 lists a comprehensive summary of the task bundling literature. Section 3 introduces the mathematical models constituting the bundling strategy. Section 4 presents the simulation of gig workers as a performance measurement of the suggested strategy. Section 5 addresses the research questions of this study through simulation-based experiments with managerial insights. Finally, Section 6 summarizes the findings of this research.

2. Literature review

While research on task bundling remains sparse, there has been some exploration in the logistics field, such as less-than-truckload (LTL) transportation and last-mile delivery. Also, similar to the scooter-charging platform, the mobile crowdsensing platform utilizes workers to perform micro-tasks, such as sensing and uploading location-specific data through the app. We provide a literature review and list the differences in our study.

Kandappu et al. (2016) first emphasized the effect of bundles in improving the detour efficiency of workers. Even with the simplicity of the experiment, valuable insights were provided considering workers' behavioral preferences and characteristics. To improve the limitations, Wang et al. (2019) proposed a bundling strategy for which many tasks and workers are considered. During each round of the collection process, the platform dynamically categorizes tasks based on their popularity and creates bundles where less popular tasks are combined with highly popular ones. Despite the increase in total worker participation, the authors point out that the simple task categorization process may worsen the system's performance.

Complementing this weakness, other studies present bundling strategies by defining a worker behavior model that formulates a probability that a worker would select a task bundle. Zhao et al. (2021) defined a worker behavior model based on factors such as the detour cost, the number of tasks within the bundle, and the spatial distribution of tasks within a bundle. The total task bundling plan, which maximizes the number of expected completed tasks, is determined. Zhen et al. (2022) suggested a worker behavior model to consider the popularity of the task inside the worker's selection probability model. A reinforcement learning approach is used to decide the final bundle set. Zhen et al. (2022) introduced a mental accounting theory to design the task execution profit and bonus. The overall incentive mechanism aims to maximize social welfare through bundles.

Meanwhile, a bundling strategy also exists within the crowdsourced delivery field. Mancini and Gansterer (2022) considered bundling customer requests for workers who deliver parcels on the way to their destinations. The auction system is adopted to assign the bundle with the highest valuation to workers. Two bundling methods are proposed: a traditional clustering-based method minimizes the maximum intra-cluster distance, and a corridor-based method bundles requests close to the direct path between the depot and the worker's destinations. Gansterer and Hartl (2018) presented a genetic algorithm-based framework to minimize a proxy objective function. This function bundles tasks to reduce tour lengths while maintaining low densities. Horner et al. (2021) presented a distinct system where workers could select a task among personalized bundles provided by the platform.

However, the bundling strategies researched thus far are difficult to apply directly due to the specific characteristics of the scooter-picking industry. Bundling strategies need to be tailored to the specific characteristics of workers and processes in each industry. Table 1 highlights how this study stands out by addressing these unique requirements within the bundling literature dealing with worker freedom.

The bundling literature covers various target fields, which yields different bundle distribution methods. In delivery platforms, including last-mile delivery and LTL transportation, there is sufficient time to assign bundles to workers, enabling distribution through auction systems. However, in mobile crowdsensing fields, bundles must be given immediately to match the timing of workers' willingness to work. This necessitates direct bundle distribution, as with the scooter charging platform addressed in this study. In such cases, it becomes crucial to establish metrics to evaluate which bundles are likely to appeal to workers before they are offered, often achieved through proxy objectives. Gansterer and Hartl (2018) were the first to propose a proxy objective for generating appealing bundles as bids, focusing on the route length and density of the bundles. Zhao et al. (2021) and Zhen et al. (2022) built upon this idea by adopting a probability-based model and a social welfare maximization model, respectively. Our study extends this concept by introducing two novel proxy objectives: the VMB model, which maximizes the reward-to-dispersion ratio using the standard distance deviation factor, and the PMB model, which employs a reward-to-probability framework based on the sensing model.

The advantage of our approach is that it requires minimal data from workers. All the information needed to generate bundles, such as depot and capacity data, is already gathered during workers' registration on the platform. This

Table 1. Comparison of literature on bundling strategy in crowdsourcing platform with worker freedom.

	Target field	Bundle distribution	Proxy objective usage	Additional data requirements	Worker type
Wang et al. (2019)	Mobile crowdsensing	Direct distribution	No	Task preference data	Not specified
Mancini and Gansterer (2022)	Last-mile delivery	Auction	No	Worker trajectory, auction feedback data	Depot-returning
Gansterer and Hartl (2018)	LTL transportation	Auction	Yes (minimization of route length and density)	Auction feedback data	Not specified
Zhao et al. (2021)	Mobile crowdsensing	Direct distribution	Yes (probability-based model)	Worker trajectory data	Depot-returning
Zhen et al. (2022)	Mobile crowdsensing	Direct distribution	Yes (social welfare maximization)	Task willingness data	Not specified
This study	E-scooter charging	Direct distribution	Yes (VMB: reward-to-dispersion ratio; PMB: reward-to-probability ratio)	No additional data needed	Depot-oriented

is a key strength, allowing for rapid implementation and direct bundle provision in fast-paced platforms such as e-scooter charging systems. On the other hand, other article needs time-consuming processes, such as auction feedback in Gansterer and Hartl (2018) and Mancini and Gansterer (2022), or additional information from workers such as travel trajectory in Zhao et al. (2021) or worker's task willingness in Zhen et al. (2022). This is impractical in the scooter-charging industry to expect workers to endure long wait times for task assignments through an auction system or feedback process. Our study is distinguished by its strength in proposing a method for bundling that operates effectively with limited information and supports convenient worker engagement.

Finally, our study focuses on depot-oriented workers, a previously unexplored group in which both the starting point and destination are the depot. In contrast, previous studies either do not specify worker types or focus on depot-returning workers (Mancini & Gansterer, 2022; Zhao et al., 2021), who start at non-depot locations and return to a depot. These studies allow platforms to use workers' trajectories as inputs for creating bundles, which is inappropriate in scooter-charging platforms. In this study, workers require vehicles with sufficient space to collect scooters and plug-in charging equipment for recharging, making their journeys inherently depot-oriented. This unique characteristic necessitates a tailored bundling strategy to meet the specific needs of depot-oriented workers.

Overall, this study proposes a bundling approach tailored for depot-oriented workers, removing the need for trajectory data. It also introduces proxy objectives to evaluate bundle attractiveness, functioning efficiently without additional information and ensuring seamless worker engagement.

3. Mathematical models

This section introduces the mathematical models and algorithms employed for each stage of the bundling strategy. The process involves two steps: first, the generation of candidate bundles, and second, the selection of winning bundles to form the final bundle set. Additionally, we present behavior models for gig workers considered during the bundling process. The proposed bundling model is applicable to industrial scenarios with the following characteristics:

- Bundle options are provided to workers before the task begins, without the need for workers' feedback on the quality of the bundles.
- Geographic proximity between locations is a key consideration.
- Workers can make multiple task reservations in sequence.
- The pick-up task involves visiting specified locations and verifying completion via an app.
- As collection and relocation happen in separate phases, relocation is beyond the scope of this model.

3.1. Gig worker's behavior

The study targets an industrial setting where it is infeasible to assign specific workers to pick up specific scooters or receive workers' preferred schedules in advance. The workers in this study have a fixed destination to return to after completing scooter collections. Workers charge the collected scooters at the destination using electric chargers received from the platform in advance. Typically, gig workers register their addresses on the platform, so we assume that this location is known to the platform.

Additionally, each gig worker is assumed to have a capacity, denoted as Q, which restricts the amount of scooters they can collect. For instance, a worker with one charger is estimated to have a capacity Q of value 100, which is sufficient to full-charge a single depleted scooter (0% battery to 100%). In practice, it usually takes an hour to fully charge a scooter with an 80% battery, while a scooter with no battery takes 5–6 hours (Helling, 2022). For simplicity, we assume that the charging profile of scooters is linearized. We allow workers to split their capacity to charge multiple scooters; workers with $Q = 100$ can fully charge two half-depleted scooters (each 50% uncharged). Therefore, Q is a measure of total available battery capacity, not the number of scooters, and workers can collect many scooters as long as they can fully charge them until the next service period. Note that if the combined capacity required to charge all scooters in a bundle exceeds Q, the corresponding worker cannot select that bundle.

We established the following two assumptions for the behaviors of an active worker in a platform. First, gig workers evaluate the attractiveness of tasks displayed on the platform according to two factors: the attractiveness of a scooter is proportional to reward and inversely proportional to the travel distance of visiting a scooter (individual option) or scooters within a bundle (bundle option) and returning to their destination. Figure 1 illustrates the evaluation of task attractiveness for each option. For the individual option, the reward is divided by the distance passing through the scooter to the worker's destination. This is because workers need to return to their destination at last, and scooters located too far away are less favorable. For the bundle option, the bundle reward, which is the sum of individual rewards, is divided by the distance of the shortest path that covers all scooter locations and the destination. As workers likely estimate distances intuitively rather than by finding the exact shortest path, we used the nearest neighbor algorithm for computational efficiency in the Experiments presented in Section 5. Then, considering attractiveness as an expression of task preference, workers select a task with the highest attractiveness value. This greedy nature is due to the competitive nature of the industry, where workers can only reserve one task at a time.

Second, the worker's cumulative activity affects whether or not to pick up the next particular scooter or bundle. Workers in this study regard gig work as a side job that brings impromptu income in their spare time. Therefore, once the workers have satisfied their quota to some extent, they may only pick up sufficiently valuable scooters and otherwise terminate. We assume this activity quota is proportional to the worker's capacity Q. To organize this setup, a worker is regarded to have threshold values for attractiveness and an activity quota, which we denote as α and β ($0 \le \alpha$ and $0 \le \beta \le 1$), respectively. Before filling up the β rate of their capacity Q, workers will greedily choose tasks with the highest attractiveness value. After that, they will only choose tasks with an attractiveness value higher than α (USD/km).

Also, we consider the following assumptions for designing the problem.

- The reward for picking up a particular scooter is given (see Section 5.1 for a detailed pricing process). In the case of a bundle, the total reward is the sum of the reward prices of all scooters in the bundle.
- There is a daily set time when workers can participate in the platform. Once workers finish working and return to their destination, they do not restart collection again on the same day.
- A worker can reserve only one task, either an individual scooter or a bundle, at a time, and the previous reservation must be completed before the next.
- Workers have no information about others, including destination or workload.
- If the attractiveness of an individual scooter provided in a bundle is worth more than the bundle, the worker is allowed only to reserve the individual scooter. Then, the provided bundle option is eliminated from the platform.

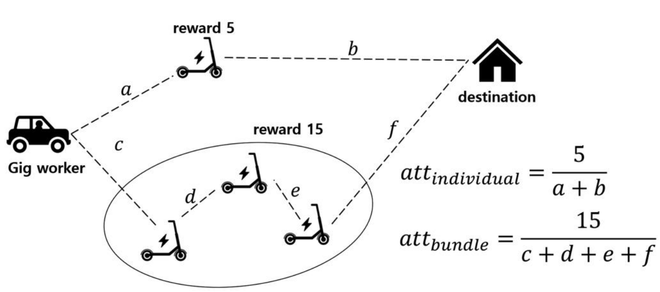


Figure 1. Attractiveness of an individual option and a bundle option (reward: USD; distance: km).

3.2. Step 1: Generation of candidate bundles by bundle generator

The approach we adopt for generating bundles consists of two distinct steps. At first, we generate a set of candidate bundles. Then, from the set of candidate bundles, we select a subset of winning bundles based on set packing models of which objectives are designed to entice workers.

Partitioning N scooters to subsets is intractable, as the case grows exponentially with the number of scooters. Also, the majority of these subsets may not be attractive to workers. Instead, we present a bundle generator capable of generating meaningful subsets of which high attractiveness comes from the relative distances of scooters.

The process starts with a target scooter and gradually adds the next available scooter until the maximum bundle size is reached. Considering workers' capacity constraints during scooter collection, we set an upper limit on the bundle size, denoted as "*MaxBundleSize*," to ensure that a bundle does not contain excessive scooters.

We present three bundle-generating rules applied uniformly to all scooter nodes, each serving as a target scooter. Each rule focuses on grouping nearby scooters by distance or statistical dispersion. In one way, we introduce standard distance deviation (Levine, 2004), which estimates the scattered degree of geographic points (see Section 3.3 for exact calculation). The three rules are as follows:

- Rule 1: Select the node nearest to the target node
- Rule 2: Select the node nearest to the last added node
- Rule 3: Select the node that least increases the standard distance deviation of a bundle

Each rule selects a new scooter node to generate new bundles, which are added to the bundle set $\mathbb{B}$. Figure 2 illustrates the scooter node selected in every iteration when three rules are applied to target scooter 13 with a *MaxBundleSize* of 5. Scooter 6 was selected under all three rules during the first iteration, but differences appeared in the subsequent iterations. Columns 2, 4, and 6 in Table 2 show this procedure in detail. Columns 3, 5, and 7 in Table 2 indicate the generated bundles in each iteration by the corresponding rule. To elaborate, the chosen scooter is merged with the target node, along with all previously formed bundles, using the same criterion. That is, $\mathbb{B}$ is the subset of the powerset of previously selected scooters with more than one element. Note that this is applicable for rules 1 and 2 but not for rule 3, as the latter emphasizes forming a bundle with only a low standard distance deviation. Every iteration updates $\mathbb{B}$, and with each one, the size of the bundle added to the bundle set increases by one. This leads to $|MaxBundleSize - 1|$ iterations for each rule per node. See Appendix A for the pseudo-code of each rule. Subsequently, duplicates are removed, leaving 32 unique bundles in the bundle set. The final candidate bundles are obtained by repeating this procedure for every scooter node.

3.3. Step 2: Selection of attractive bundles by set packing models

So far, bundles generated through a generator may share the same scooter. For example, it is observed that scooter number 13 is assigned to all bundles in Table 2. The next step is to sort out a combination of bundles to ensure that no individual scooter is included in multiple bundles.

We developed two set packing models that find the winning bundles among the candidates. One is the VMB model, which maximizes the sum of the total value of bundles, and the other is the PMB model, which maximizes the sum of the probability of a bundle being selected. Notations for the models are denoted in Table 3. The solution of the models

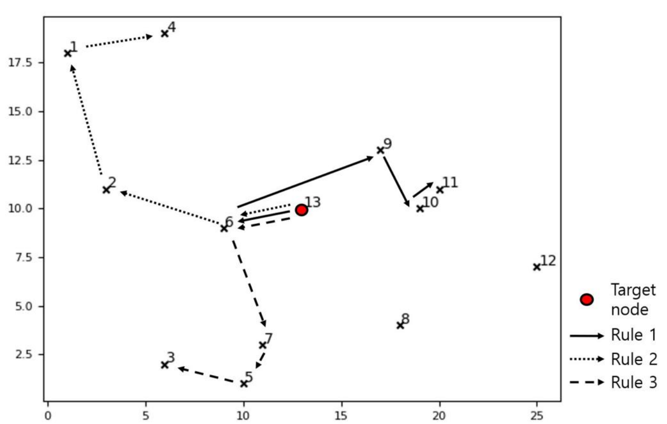


Figure 2. Iterative addition of scooters by each bundle generating rule applied to a target scooter 13.

will be offered as bundle options to workers. Additionally, the scooter, not in any of the winning bundles, is given as an individual reservation option, which is still available for workers to collect. The key distinction between the VMB and PMB models is that the VMB focuses on maximizing bundle value based on scooter data alone, while the PMB accounts for the worker's depot location.

The VMB model can be formulated as follows:

$$\max \sum_{j\in B} \left(\frac{P_j}{std_j}\right) x_j \tag{1}$$

$$\text{s.t.} \sum_{j\in B} a_{ij}x_j \le 1 \qquad \forall i \in N \tag{2}$$

$$x_j \in \{0,1\} \qquad \forall j \in B \tag{3}$$

The objective function (1) maximizes the sum of the value of bundles, calculated by $\frac{P_j}{std_j}$. Here, we model that the value of a bundle j is proportional to the total bundle reward, P_j (the sum of the individual rewards of included scooters), and is inversely proportional to the standard deviation of the distances of the included scooters, std_j. The std_j for a bundle j including $n(\ge 3)$ scooters with coordinates $(e_1, l_1), \ldots, (e_n, l_n)$, is calculated as follows: $std_j = \sqrt{\sum_{i=1}^{n} \frac{(E-e_i)^2+(L-l_i)^2}{n-2}}$ where $E = \sum_{i=1}^{n} e_i$ and $L = \sum_{i=1}^{n} l_i$. In the case of a bundle size of two, std_j is simply the distance between two points. Constraint (2) ensures that no scooter is included in more than one winning bundle.

The attractiveness of each task changes because workers select the next task after completing the current one, and the worker's location changes accordingly. In this perspective, the VMB model generates attractive bundles irrespective of the worker's location. On the other hand, the PMB model considers workers' destinations when creating bundles, as workers tend to return to their respective locations after completing tasks. This approach recognizes that a worker's perception of a bundle's value can be influenced by the distance to the worker's depot.

To address this issue, we introduce the parameter Pr_{jk}, the probability of a bundle j being selected by a worker k. We assume that Pr_{jk} is influenced by P_j, std_j, and the distance between the worker's destination and the bundle

Table 2. Demonstration of bundles added to candidate bundle set $\mathbb{B}$ with a target scooter 13.

	Rule 1		Rule 2		Rule 3	
	Scooter	Bundle	Scooter	Bundle	Scooter	Bundle
Iteration 1	6	(13, 6)	6	(13, 6)	6	(13, 6)
Iteration 2	9	(13, 9), (13, 6, 9)	2	(13, 2), (13, 6, 2)	7	(13, 6, 7)
Iteration 3	10	(13, 10), (13, 6, 10), (13, 9, 10), (13, 6, 9, 10)	1	(13, 1), (13, 6, 1), (13, 2, 1), (13, 6, 2, 1)	5	(13, 6, 7, 5)
Iteration 4	11	(13, 11), (13, 6, 11), (13, 9, 11), (13, 6, 9, 11), (13, 10, 11), (13, 6, 10, 11), (13, 9, 10, 11), (13, 6, 9, 10, 11)	4	(13, 4), (13, 6, 4), (13, 2, 4), (13, 6, 2, 4), (13, 1, 4), (13, 6, 1, 4), (13, 2, 1, 4), (13, 6, 2, 1, 4)	3	(13, 6, 7, 5, 3)

Table 3. Notations for the VMB and PMB models.

N	Set of scooter nodes (1, …, n)
B	Set of candidate bundles (1, …, j)
K_D	Set of gig workers' depot nodes ($n+1$, …, n + k)
P_j	Reward of bundle j, $\forall j \in B$
std_j	Standard distance deviation of bundle j, $\forall j \in B$
λ	Decay parameter
δ	Distance limitation parameter
d_{jk}	Distance between the worker k's depot and the bundle centroid j, $\forall j \in B$, $\forall k \in K_D$
a_{ij}	Parameter which is 1 if bundle j contains scooter i, otherwise 0, $\forall i \in N$, $\forall j \in B$
x_j	Binary decision variable which is 1 if bundle j is selected as winning bundle, otherwise 0, $\forall j \in B$

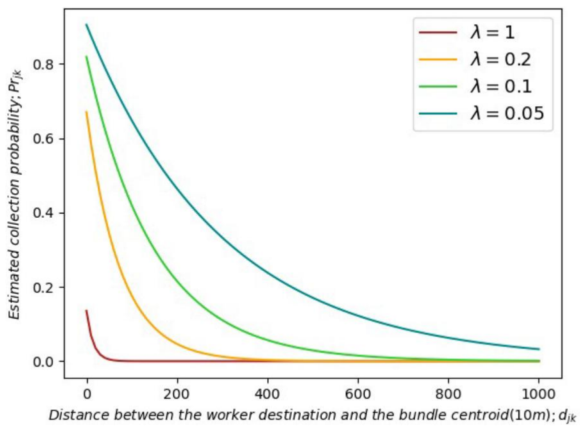


Figure 3. Collection probability Pr_{jk} of gig worker according to λ.

centroid, denoted by d_{jk}. We design the term based on the Elfes sensing model (Elfes, 2013), which models the probability of a sensor detecting an object using an exponential distribution function with a decay parameter, λ. Given that workers are capable of sensing tasks within a distance δ, Pr_{jk} can be designed as such:

$$Pr_{jk} = \begin{cases} \exp\left(-\lambda * \dfrac{d_{jk} + std_j}{P_j}\right), & \text{if } d_{jk} \le \delta. \\ 0, & \text{otherwise.} \end{cases}$$

Figure 3 depicts Pr_{jk} according to d_{jk} (P_j and std_j are fixed to 15 USD and 0.3 km, respectively). Pr_{jk} decreases as d_{jk} increases, even if bundles have the same P_j or std_j. The rate at which Pr_{jk} decreases is determined by λ, with a smaller value indicating a slower decrease. As the value of λ is larger, the model considers the probability of a worker showing interest in the corresponding bundle to be lower.

Finally, the PMB model is formulated as follows:

$$\max \sum_{j \in B} \left(1 - \prod_{k \in K} (1 - Pr_{jk})\right) * x_j \tag{4}$$

$$\text{s.t.} \sum_{j \in B} a_{ij} x_j \le 1 \qquad \forall i \in N \tag{5}$$

$$x_j \in \{0, 1\} \qquad \forall j \in B \tag{6}$$

The objective function (4) maximizes the total probability that at least one worker will choose a given bundle. Constraints (5) and (6) are the same as Constraints (2) and (3).

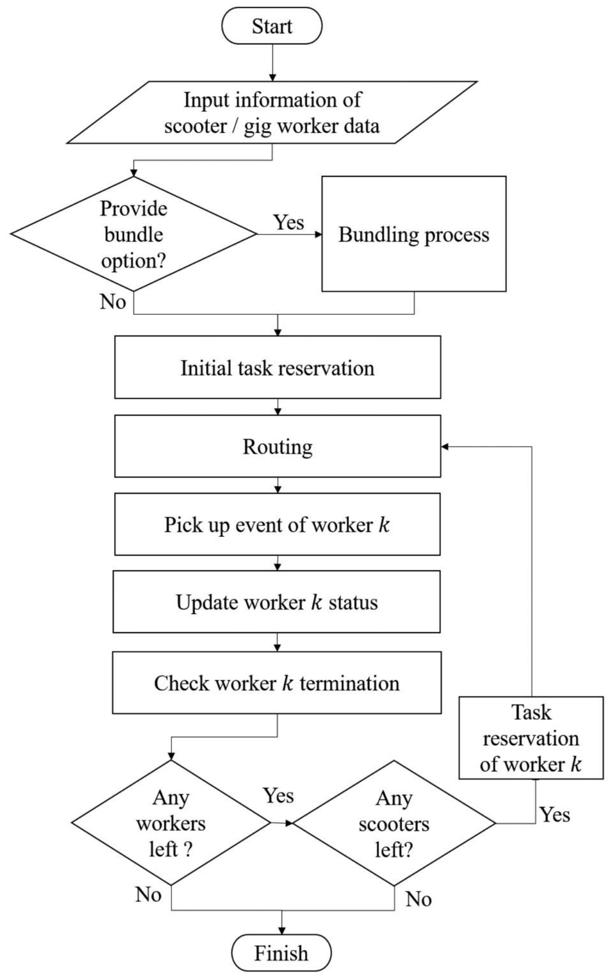


Figure 4. Flowchart of simulation.

4. Simulation model

This study proposes a simulation system of gig workers collecting the scooters. The flowchart in Figure 4 outlines the simulation process.

There are two preparation steps to complete before running the collection. First, the model requires scooter information, including the location, the required battery charge, and the reward. The model also requires information on gig workers, which comprises the depot location, the capacity, and the behavior parameters α and β. We assume that each worker's unique depot serves as the origin and destination point for that worker's collection tasks. Next, the model determines whether or not to apply the bundling process reviewed in Section 3. If applied, the bundling process is executed to provide bundles of tasks; otherwise, workers can only reserve individual scooters.

In the *Initial task reservation* step, workers reserve tasks based on the behavior explained in Section 3.1, based on the first-come, first-served rule. In case of overlapping reservations, the system randomly selects one worker. Then, the reserved tasks disappear from the platform.

During the *Routing step*, the distance of each worker to reach their designated task is calculated. Assuming that workers travel at the same speed, we can track the task completion time.

When a worker k is identified as the one who requires the shortest time to complete a task, a *pick-up event* is triggered, and the *Update status step* is executed. This step involves updating the information for the worker k, such as the accumulative capacity, the travel distance, and the reward. Additionally, for other workers who are still en route to their designated tasks, the remaining time until they reach their tasks is reduced by the according amount of time taken by worker k.

Then, the *Check worker termination* step is carried out to determine whether worker k leaves the platform. If any of the two conditions are met, we assume that the worker leaves the system: (1) a worker's remaining capacity cannot accommodate any available tasks; (2) a worker's accumulated capacity exceeds β, and there are no scooters with a value greater than or equal to α remaining for collection.

At the end of each cycle, we check if any workers or scooters are still available on the platform. If workers and scooters remain, a worker k selects the next task and the simulation proceeds with the *Routing step*. The simulation continues until no workers or scooters remain on the platform.

5. Computational experiments

We present simulation-based experiments to examine the effectiveness of the proposed bundling strategy. Each experiment addresses the following research questions:

- To what extent can bundling improve the collection rate of scooters compared to a no-bundling case?
- Dividing the scenarios according to the spatial distribution of scooters and the overall worker capacity, in which scenario is the bundling system most effective?
- How does the variability in gig worker supply change the effect of bundles on the platform and workers?
- How do key factors in the simulation process impact the performance of the bundles?

The experiments were conducted on a workstation with an Intel ®Pentium CPU G3250 at 3.20 GHz, and the optimization models were solved using ILOG CPLEX solver 12.10.

5.1. Instance generation

The simulation instances consist of data such as the map size, scooter, and gig worker details. Due to the lack of public scooter and worker data for security reasons, most of the data was generated manually. The scooter data for the experiment was generated in the following manner.

- Location of scooters: We use the generic geographic distributions presented in Solomon (1987). The location of scooters is generated based on either random or clustered patterns, and they reflect the scenario in which some scooters are clustered around bus or metro stations. In contrast, others are randomly scattered throughout the area. In each experiment, the exact ratio of scooters generated by each distribution is specified.
- Reward pricing of scooters: In practice, such as Lime scooters, the proximity of scooters is the main factor in determining the individual reward (Helling, 2022). For Lime, the reward for a single scooter typically amounts to 5 USD and seldom surpasses 12 USD (Helling, 2023). To mimic this, we use a density-based spatial clustering of applications with noise (DBSCAN) clustering method to assign rewards based on the result (Ester et al., 1996). Specifically, we use the parameters Eps = 50 and MinPts = 5. Scooters that are part of a dense cluster of at least five other scooters within a 500-m radius are considered "core" and assigned a reward of 5 USD. Scooters that are outliers and not part of any cluster are considered "noise" and assigned a reward of 10 USD. Finally, the scooters on a cluster's border are considered "border" and assigned a reward of 8 USD.
- Battery level of scooters: It is randomly chosen from a set of integers ranging from 10% to 80%, with increments of 10%.
- *MaxBundleSize*: The baseline is set to 5.

The gig worker data is generated as follows. The locations of workers' destinations are randomly generated. Also, we assume that workers' initial participation starts from their depot for every experiment for consistent analysis. We assume that all workers' parameters, such as capacity, attractiveness, and activity quota threshold, are identical within an experiment. We use a baseline value of $Q = 600\%$, $\alpha = 3$ USD/km, $\beta = 0.5$ for Experiment 1, and $\alpha = 5$ USD/km for other experiments.

5.2. Experiment 1: Effect of bundles on the collection rate

We demonstrate the effectiveness of bundles in increasing the total collection rate compared to the no-bundling case by turning on and off the *Bundling process* in the simulation. The instance used in this experiment consists of a map with an area of 5 km^2, two workers, and 25 scooters. The scooter locations consist of two clusters of 10 scooters each and five randomly placed scooters. A total of 42 instances were generated with randomness and tested independently.

The result is displayed in Figure 5 using box plots. We utilize both the VMB and PMB for the bundling models, with four different types of PMB models according to λ. As can be seen from the figure, the bundling models have a significant impact on increasing the total collection rate.

We observe that every bundling model beats the no-bundling setting.

To further emphasize the effect of the bundling strategy, we propose another comparative model, the platform intervention in the no-bundling (PI-NB) model. In bundling and no-bundling cases, gig workers can select tasks and prioritize those with higher attractiveness. However, the PI-NB model disregards this greedy behavior and instructs gig workers to achieve the maximum collection rate for a no-bundling case. To increase the collection rate, the route of PI-NB initially instructs a worker to collect scooters that are not attractive. By doing so, it is more likely that scooters will still be available that satisfy the gig worker's condition of only collecting tasks with attractiveness equal to or greater than the threshold once the cumulative capacity exceeds the activity quota.

Although this model may not be a realistic approach, it can serve as an indicator to gain insights into the effects of bundles. Based on the multi-depot capacitated vehicle routing model, PI-NB provides the route of each worker that achieves the maximum collection rate. PI-NB is formulated as follows:

$$\max \sum_{i\in V}\sum_{j\in V}\sum_{k\in K} z_{ij}^k \tag{7}$$

$$\text{s.t.} \quad z_{ii}^k = 0, \forall i \in V, \ \forall k \in K \tag{8}$$

$$z_{ij}^k = 0, \forall (i,j,k) \in \Pi \tag{9}$$

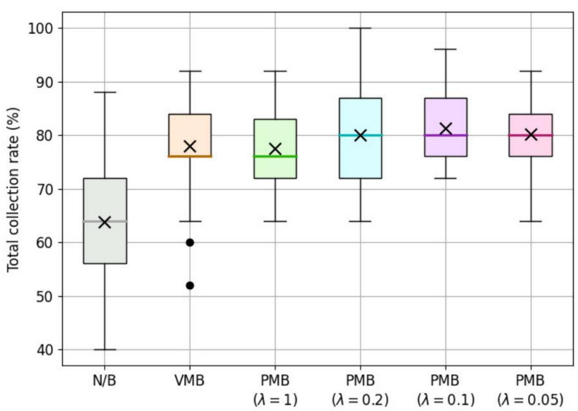


Figure 5. Box plot of the collected number of scooters according to bundling models compared to the no-bundling case.

$$\sum_{j\in N} z_{ij}^k \le 1, \qquad \forall i \in K_D, \forall k \in K \tag{10}$$

$$\sum_{i\in N} z_{ij}^k \le 1, \qquad \forall j \in K_D, \forall k \in K \tag{11}$$

$$\sum_{p\in V} z_{pi}^k = \sum_{t\in V} z_{it}^k, \qquad \forall i \in N, \forall k \in K \tag{12}$$

$$\sum_{i\in V}\sum_{k\in K} z_{ij}^k \le 1, \qquad \forall j \in N \tag{13}$$

$$\sum_{j\in V}\sum_{k\in K} z_{ij}^k \le 1, \qquad \forall i \in N \tag{14}$$

$$u_i^k = 0, \qquad \forall i \in K_D, \forall k \in K, i = k \tag{15}$$

$$u_i^k + q_j \le u_j^k + M(1 - z_{ij}^k), \qquad \forall i \in V, \forall j \in N, \forall k \in K \tag{16}$$

$$u_j^k \le M * \sum_{p\in V} z_{pj}^k, \qquad \forall j \in N, \forall k \in K \tag{17}$$

$$u_i^k - Q * \beta \le M(1 - z_{ij}^k), \qquad \forall i \in V, \forall k \in K, \forall j \in A_i^k(\alpha) \tag{18}$$

$$z_{ij}^k \in \{0,1\}, \qquad \forall i,j \in V, \forall k \in K \tag{19}$$

$$u_i^k \ge 0, \qquad \forall i \in V, \forall k \in K \tag{20}$$

The notations are explained in Table 4 (notations listed in Table 3 are excluded). The objective function (7) maximizes the total number of collected scooters. Constraint (8) ensures no travel from a node to itself. Constraint (9) prohibits a worker from visiting another worker's depot. Constraints (10) and (11) ensure that each worker can leave and return to the depot only once. Constraint (12) is a balance equation. Constraints (13) and (14) specify that each node can be visited by at most one worker or not visited at all. Constraint (15) makes a worker's capacity start from zero. Constraint (16) enforces an accumulated capacity to increase by q_j when a worker k visits node j immediately after visiting node i. Constraint (17) specifies that the accumulated capacity of worker k at node j is equal to zero if the worker does not visit that node. Constraint (18)

Table 4. Notations for the PI-NB model.

K	Set of gig workers $(n+1, \ldots, n+k)$
V	Set of total nodes, $N \cup K_D$ $(1, \ldots, n+k)$
Π	Set of arcs that connect workers to visit other workers' depot nodes $= \begin{cases} (\forall i \in K_D, \forall j \in V, \forall k \in K, i \ne k) \\ \cup(\forall i \in V, \forall j \in K_D, \forall k \in K, i \ne k) \end{cases}$
M	Large number
r	Small number
Q	Capacity of a worker
p_j	Reward of scooter j, $\forall j \in N$
q_j	Battery charge required for scooter j, $\forall j \in N$
α	Threshold value of task attractiveness
β	Threshold value of activity quota
$A_i^k(\alpha)$	Set of scooters with value under than α for worker k right after visiting node i, $\forall i \in N$, $\forall k \in K$
z_{ij}^k	Binary variable which is 1 if worker k visits node i to j, otherwise 0, $\forall i \in V$, $\forall j \in V$, $\forall k \in K$
u_i^k	Accumulated capacity of worker k at node i, $\forall i \in V$, $\forall k \in K$

prohibits workers whose accumulated capacity exceeds β from accepting tasks with an attractiveness below α. By applying this constraint, the workers are directed to visit scooters with lower values before those with higher values. Constraint (19) is the binary constraint, and Constraint (20) is the positive of the capacity variable. See Appendix B for additional Constraints (B1) and (B2).

Figure 6 plot represents the relative collection rate of each bundling compared to the comparative PI-NB model, which is set to 100. For instance, if the PI-NB model obtained a result of 25 while the VMB model obtained 22, the box plot value is $100 - (25-22) \times 100/25 = 88$. We present multiple models with varying λ values for the PMB model. The findings indicate that bundling models are effective in increasing the collection rate compared with the no-bundling (box plot N/B) case. Moreover, the result of bundling models is notably closer to the result of the PI-NB model. On average, 70% is collected without bundles; however, it increases to almost 90% with bundles. We illustrate this point using Figure 7.

Figure 7 illustrates the difference in workers' routes of no-bundling, bundling models, and the PI-NB model setting as an example. Figure 7a shows that only 10 out of 25 scooters are collected without bundling. However, Figure 7b shows that when using the PMB model, eight bundles are

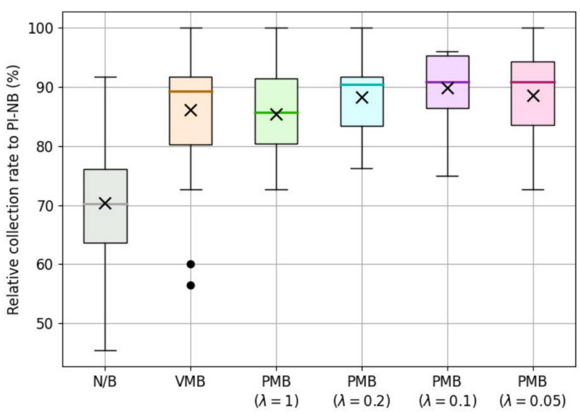


Figure 6. Relative collection rate normalized to the maximum collection of PI-NB.

generated, resulting in the collection of 21 scooters. Finally, Figure 7c demonstrates that 22 scooters can be collected if the platform directly manages the workers without bundling (i.e. an ideal PI-NB model).

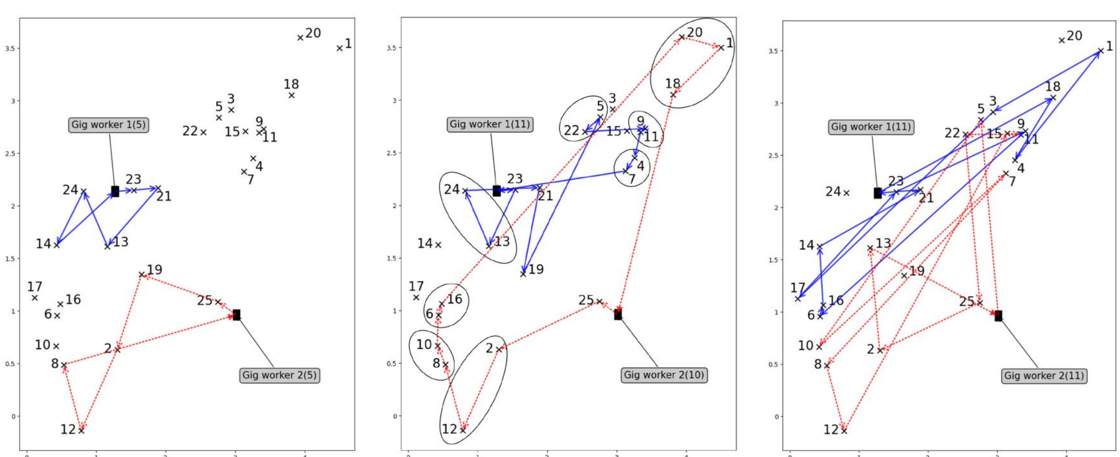
From Figure 7, it is intuitive that bundles encouraged workers to participate beyond their usual activity quota. In Figure 7a, worker 2 returns home immediately after collecting scooter 8. In contrast, in Figure 7b, the worker continues collecting after scooter 8, taking the opportunity to collect the bundle of scooters 6 and 16 without depriving them. This increases the value of the task, encouraging the worker to proceed with further collection. Additionally, the bundles enable the collection of scooters distributed in the upper-right region, which were not collected in Figure 7a, thereby improving the overall collection rate. As a result, as shown in Figure 6, the bundling models significantly outperform the no-bundling setting.

Furthermore, among the bundling models, there are instances where the collection rate reaches the level of the ideal PI-NB model. The results of the PI-NB model, as shown in Figure 7c, represent unrealistic outcomes that would require workers to be explicitly directed to prioritize long-distance tasks. However, introducing bundles achieves nearly 90% of the PI-NB results. This is achieved even when workers make autonomous decisions, demonstrating the effectiveness of the 2-stage bundling algorithm.

5.3. Experiment 2: Scenario-based experiments on the bundling performance

The experiment investigates the performance in different scenarios categorized by two features: (1) the spatial distribution of scooters and (2) the overall worker capacity. The instances used in this experiment consist of a map with an area of $14\,km^2$, 10 workers, and 150 scooters. We generated 40 instances for each scenario.

The scenarios are denoted using the following notations: R or C to indicate a uniformly random or clustered distribution of scooters, respectively, and J or S to denote the overall charging capacity of workers and the overall battery required



(a) No-bundling. (b) Bundling. (c) PI-NB.

Figure 7. Comparison of collection results for a sample instance of experiment 1.

to charge every scooter fully. For example, an instance denoted by *C100_R50* and *J2000_S7500* implies that 100 out of 150 scooters were generated using the clustering technique, and the total charging capacity of workers and total scooter charging requirement were 2000% and 7500%, respectively. We set the overall battery amount required to charge every scooter to 7500% for all scenarios.

Figure 8 depicts the collection efficiency according to the overall worker capacity. As the overall battery charge required for fully charging the scooters is fixed at 7500%, it is clear to identify the effect of the overall worker capacity. Each box plot illustrates the distribution of 40 instances of the total collection rate in Figure 8a and the improvement rate in Figure 8b. The improvement rate indicates how much the collection rate was increased by implementing the relevant bundling techniques compared to the no-bundling case.

Figure 8a indicates that the collection rate increases as overall worker capacity rises, as expected. However, Figure 8b highlights an interesting difference between the bundling options regarding the improvement rate. Specifically, when overall worker capacity is low, bundling options have minimal differences. In some cases, the collection rates are even lower than in the no-bundling case. This happens when workers often lack sufficient capacity to physically collect scooters, even when bundling offers a valuable alternative. In some cases, without bundling, workers may collect one or two additional scooters individually due to differing collection routes, which can occasionally lead to better outcomes in the no-bundling scenario. Nevertheless, as the worker capacity increases, the PMB models demonstrate superior performance over the VMB model. In general, PMB models with λ values of 0.2 and 0.1 exhibit higher superiority. It reveals that utilizing the worker's depot information yields better collection rates especially when λ is calibrated properly.

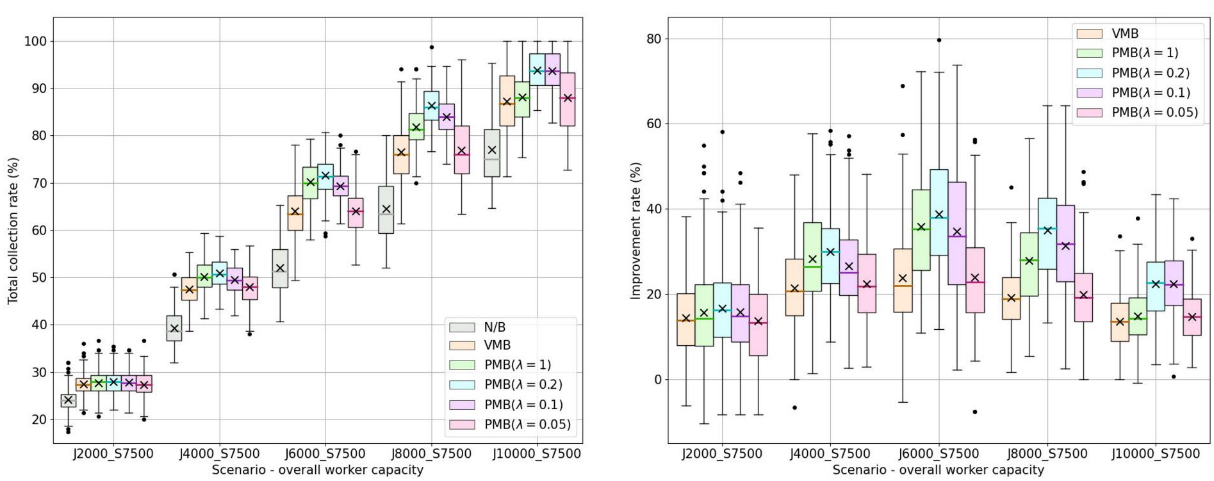
Another interesting observation is that the improvement rate is highest when the overall gig worker capacity and the overall charging requirements of scooters are close together. This is because when the realistic collectible capacity of workers is too low, the workers' capacity can quickly become full, reducing the impact of bundling. Conversely, when the collecting power of gig workers is much higher than the scooters available for collection, the improvement rate can also be lower because the number of scooters that workers collect from the no-bundling case is already substantial.

Figures 9 and 10 depict the outcome according to the spatial distribution of scooters. On each graph, the x-axis represents a more randomized distribution of scooter locations as it moves toward the right. Our analysis indicates that the spatial distribution of scooters and the overall worker capacity influence the collection rate. Upon analyzing Figures 9a and 10a, we observed minimal variation in the distribution; however, as the worker capacity increases, the differences in the collection rate become more noticeable.

As depicted in Figure 9b and c, there is a declining trend in the no-bundling case, indicating that the total collection rate decreases when scooters are less clustered. However, Figure 10b and c reveal that bundling models substantially influence random scooter distribution. The two following ideas can be inferred from this observation. The first is that when the overall capacity of gig workers is sufficient, the collection rate drops notably as the spatial distribution of scooters becomes more random instead of clustered. This phenomenon is especially evident in the no-bundling case. The rationale behind this is that the scooters are closer in a clustered arrangement, making it easier for workers to spot attractive scooters. The second is that bundles efficiently compensate for this gap in random distributions by increasing the task attractiveness. Especially the experiment finds the superiority of PMB models with moderate λ values of 0.1 and 0.2. This highlights that even though the VMB model exhibits a constant improvement rate, PMB models with appropriately calibrated parameters can accelerate the performance.

5.4. Experiment 3: Real data implementation under varying gig worker supply

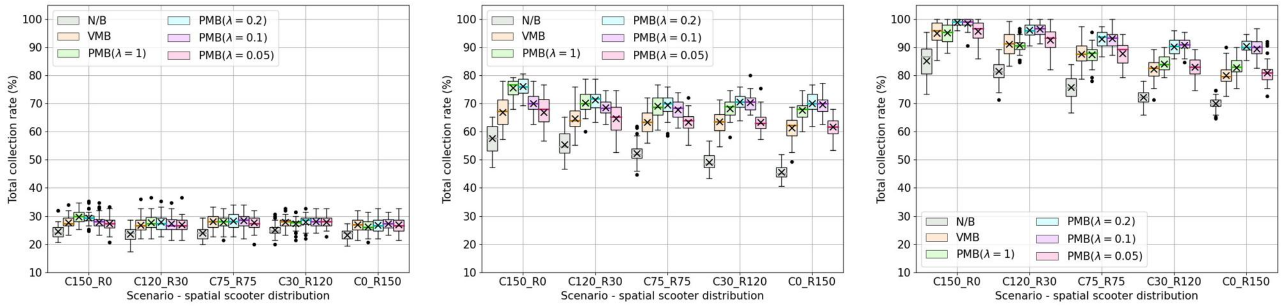
This experiment examines the bundling benefits to gig workers by increasing their profit margins. To conduct the



(a) Total collection rate.

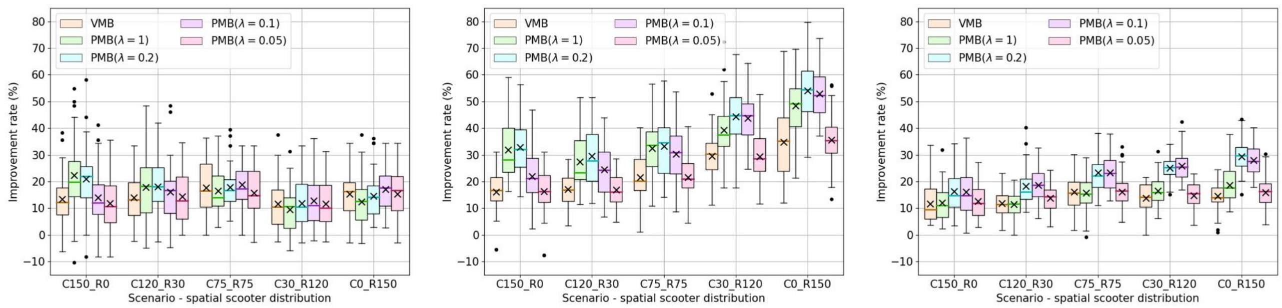
(b) Improvement rate by bundles.

Figure 8. Collection efficiency according to overall worker capacity.



(a) *J2000_S7500*. (b) *J6000_S7500*. (c) *J10000_S7500*.

Figure 9. Comparison of the total collection rate under the spatial distribution of scooters.



(a) *J2000_S7500*. (b) *J6000_S7500*. (c) *J10000_S7500*.

Figure 10. Comparison of the improvement rate under the spatial distribution of scooters.

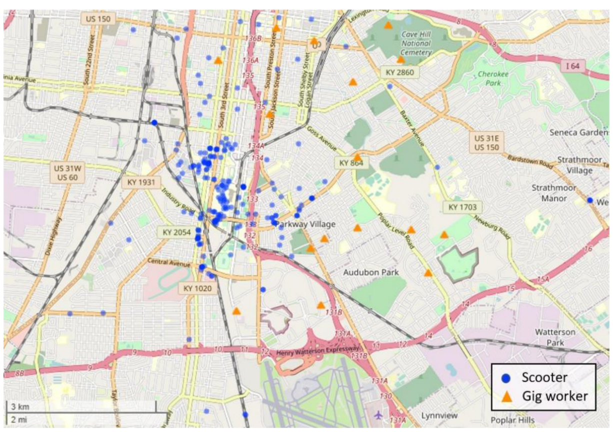


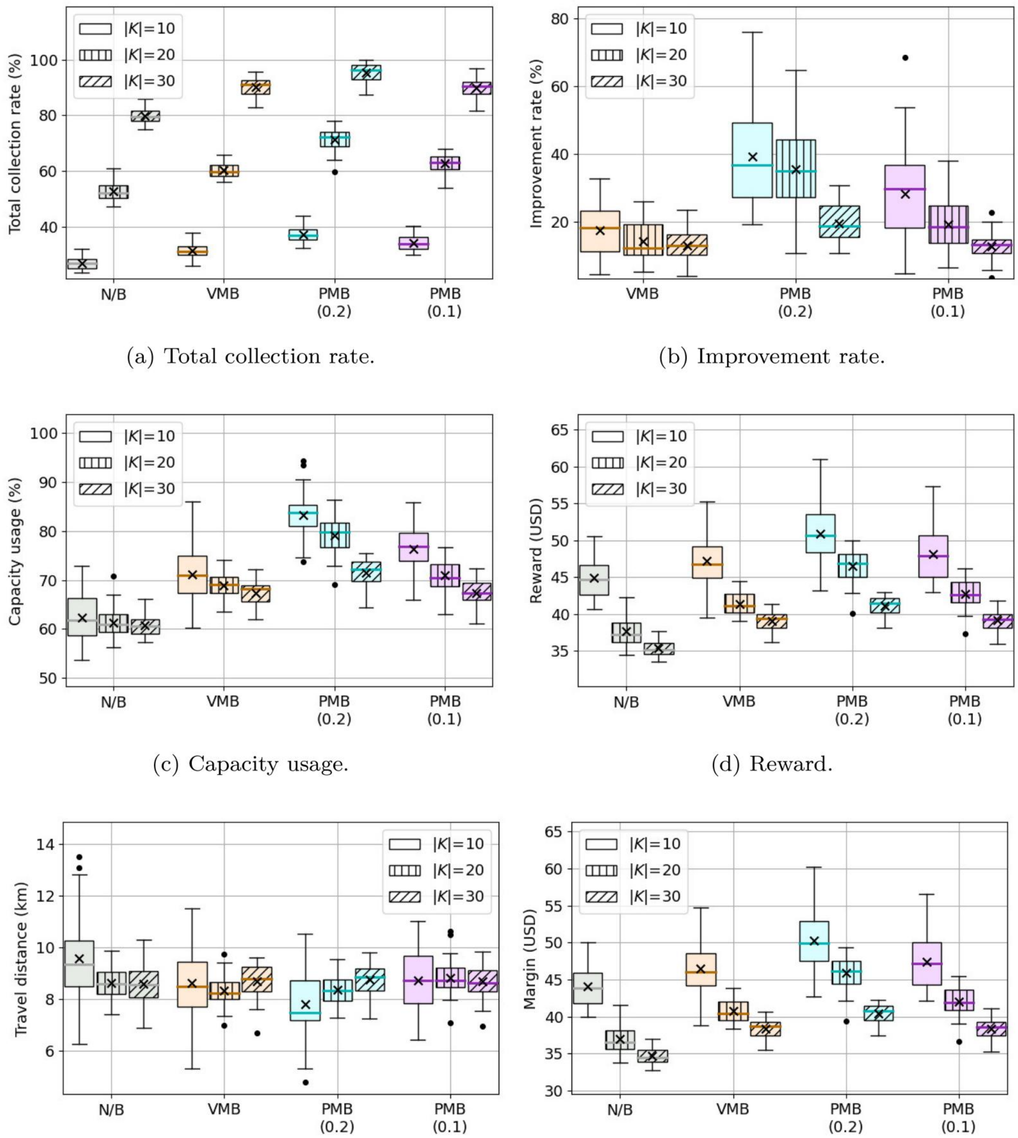
Figure 11. Geographical distribution of scooters and gig workers.

analysis, we utilized open data from Louisville, Kentucky, in the US, which consisted of the latitude and longitude information of stationary scooters from multiple companies. The realistic distribution of scooter geospatial information was referenced using this data. Among them, 228 scooters located in the core area were used for the experiment, and their distribution is visually represented in Figure 11. The battery status of the scooters was randomly generated based on a uniform distribution of U[10, 80]. Also, the destinations of the workers were randomly generated to be located in their place of residence. Figure 11 shows the distribution for a group of 30 workers.

We examine the impact of bundling on gig worker supply by varying the number of participating workers ($|K| = 10, 20, 30$). Figure 12 presents the simulation results for no-bundling, VMB, and two PMB models with λ values of 0.2 and 0.1. Each boxplot represents the average of 40 instances with different worker locations. The *MaxBundleSize* of bundling models is set to 5, and Q is homogeneous to 500%. Additionally, α and β of workers are sampled from uniform distributions *U*[4.5, 5.5] and *U*[0.4, 0.6], respectively.

In Figure 12a, for every model, the collection rate increases with the number of workers. This result is expected because of the workers' limited capacity. When the gig worker supply is comparatively sufficient ($|K| = 30$), the PMB model with $\lambda = 0.2$ raises the collection rate to over 90%, while it remains around 40% during a shortage ($|K| = 10$). Nonetheless, the findings in Figure 12a show that bundles always increased the total collection rate compared to no-bundling, shown by the positive improvement rates.

Remarkably, the bundling effect was stronger when gig worker supply was limited. In Figure 12b, the improvement rate was higher when there were fewer gig workers, suggesting that the bundling models encouraged workers to fully utilize their capacity during shortages. This inference is further supported by Figure 12c, which shows the average capacity usage of workers. In the no-bundling case, the workers' capacity usage of around 60% suggests that they rarely encounter attractive scooters after fulfilling their activity quota, causing them to terminate early. On the other hand, the bundling models significantly increased the workers' capacity usage over the β, indicating that bundles stimulated their collection activity. For instance, the PMB ($\lambda = 0.2$) increased workers' capacity usage nearly up to 85% when $|K| = 10$. Meanwhile, the declining trend in the improvement rate as $|K|$ increases may be due to the



(a) Total collection rate.

(b) Improvement rate.

(c) Capacity usage.

(d) Reward.

(e) Travel distance.

(f) Profit margin.

Figure 12. Simulation metrics according to gig worker supply levels.

competition effect, as many workers have already preempted the bundles by selecting high value options. As a result, compared to when $|K|$ is smaller, the total number of scooters available for collection decreases, making the improvement rate appear less significant.

Additionally, Figure 12f demonstrates that the workers achieved a higher average profit margin with the adoption of bundles. This is evidenced by the higher reward per distance traveled in Figure 12d and e. The cost per kilometer is approximated to be 0.08 USD. A higher worker profit margin implies a greater revenue earned per unit distance traveled, indicating that workers were provided with high-value alternatives through bundling. Thus, in situations where the workforce relies on gig workers, we demonstrated that bundling can partially address the instability of worker supply by improving both collection rates and worker margins.

5.5. Experiment 4: Sensitivity analysis

This section provides a sensitivity analysis of the parameters that impact the simulation result. For the platform, *MaxBundleSize* is an endogenous factor in defining the candidate bundles in Step 1 of our approach. As exogenous factors, the workers' threshold values for the collection attractiveness, α, and the activity quota, β, can change the collection outcome significantly. We observed the changes in simulation outcomes by adjusting the values of these parameters within realistic ranges. The experimental data of 40 instances is the same as in Experiment 3. The baseline setting is as follows: $|K| = 20$, *MaxBundleSize* is set to 5, α is sampled from $U[4.5, 5.5]$, and β is sampled from $U[0.4, 0.6]$. Each sensitivity analysis was conducted by adjusting one parameter at a time while the others remained fixed at baseline values.

Figure 13 shows the impact of the *MaxBundleSize*. The result for each size is illustrated as the pattern of the boxplot. In Figure 13a, the total collection rate by size differs among models. For the PMB model with $\lambda = 0.2$, there was a notable increase between sizes 3 and 5. The phenomenon is explained by the increase in the number of candidate bundles due to the larger *MaxBundleSize*. This enables the bundling model to improve the likelihood of selecting more attractive bundles among diversified candidates. It can be inferred that the objective function of the PMB model well selected the bundles that were actually effective for workers.

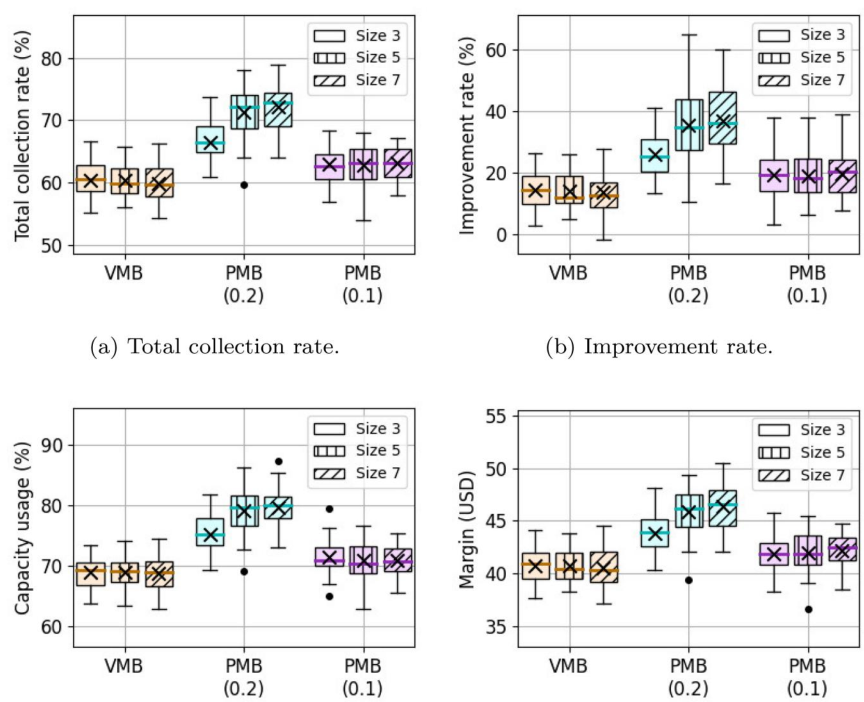
On the other hand, there was no significant difference in the collection rate for the VMB and PMB models with $\lambda = 0.1$ across sizes. The reasoning for this is that there is a limit to the extent to which *MaxBundleSize* can improve the collection rate. Despite the fact that the candidate bundles are diversified, larger bundles generally require longer detours for workers. As this is less attractive for workers, it lowers the possibility of being selected by the VMB and PMB. Thus, the final bundles are highly likely to have a much smaller size than the *MaxBundleSize*. As a result, the improvement rate in Figure 13b shows less difference between sizes. The PMB ($\lambda = 0.2$) also encounters this phenomenon by showing less improvement in sizes 5 to 7 than in sizes 3 to 5.

Meanwhile, as the bundle size increases, there is a risk of placing a greater collection burden on workers in terms of capacity, which could lower the improvement rate. The VMB model with size 7 in Figure 13b shows this example. However, the encouraging aspect is that despite this risk, the improvement rate did not significantly decrease for most cases. This reaffirms that the VMB and PMB models effectively maintain efficiency by selecting attractive bundles during the selection process. In other words, it demonstrates that the collection rate can be maintained above a certain level through appropriate filtering, without unnecessarily expanding the bundle size. Figure 13c and d also show a similar pattern in the workers' metrics, with capacity usage and margin presented in each figure, respectively.

Figure 14 reveals the impact of the parameters α and β. The x-axis displays the mean values of the uniform distributions from which α and β are sampled. α is evaluated at four levels and β at three, resulting in 12 combinations. The results are displayed in boxplots, with each model evaluated over 40 instances. For the same instance, other worker attributes, such as depot location and capacity, are kept constant, with only the α or β being varied. The line plot in Figure 14 connects the averages of the PMB ($\lambda = 0.2$) model with equal β.

Figure 14a illustrates the pattern of the total collection rate. The consistent trend across models shows that the collection rate increases as the β rises, supporting the assumption that workers utilize more capacity with higher β. This is further confirmed in Figure 14c, where workers' average capacity usage exceeds the β.

Additionally, Figure 14a reveals that, when comparing cases from $\alpha = 3$ to $\alpha = 9$, the collection rate decreases as the α increases. This aligns with the assumption that workers become more selective after reaching their β capacity threshold. The line plots also show that the reduction between consecutive α levels diminishes as the level increases. While workers easily find bundle options with values greater than $\alpha = 3$, it becomes increasingly challenging as α increases. This suggests that bundles can only motivate workers up to a certain point, based on α levels. A similar



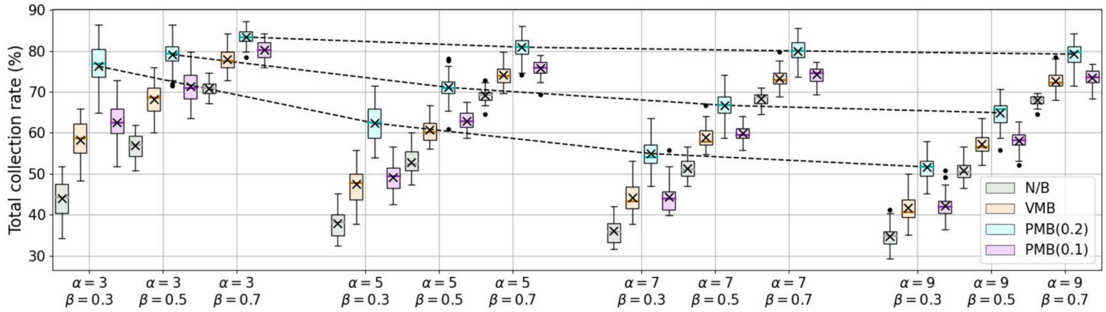
(a) Total collection rate.

(b) Improvement rate.

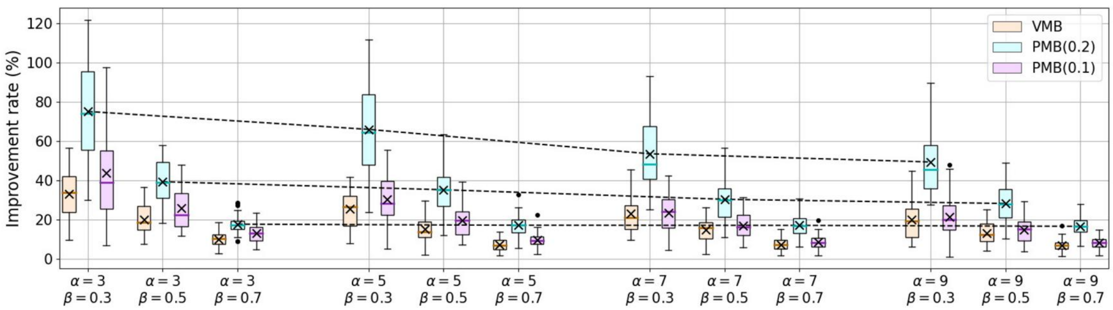
(c) Capacity usage.

(d) Reward.

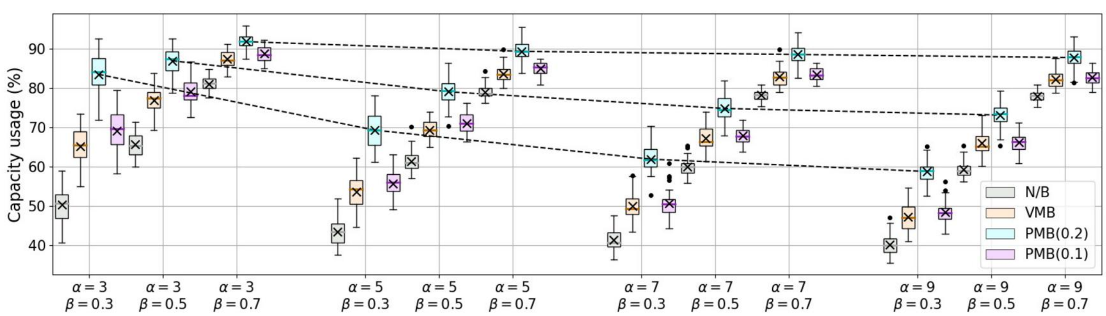
Figure 13. Simulation metrics according to *MaxBundleSize*.



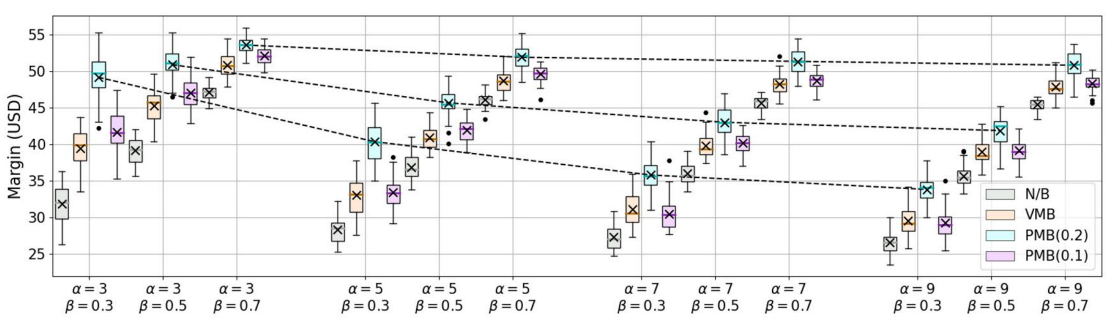
(a) Total collection rate.



(b) Improvement rate.



(c) Capacity usage.



(d) Margin.

Figure 14. Simulation metrics according to α and β.

trend is observed in the improvement rate, as shown in Figure 14b.

According to Figure 14d, a promising observation is that workers' margins are higher across all combinations of α and β in the bundling scenarios compared to in the no-bundling case, as is the collection rate. Generally, workers with higher β earn greater margins, regardless of α, as shown by the line plot—where the margin gap widens at lower β. A lower β represents workers who are less inclined to fully utilize their capacity. Thus, the larger margin gap between no-bundling and bundling models at lower β suggests that bundles are particularly effective in motivating more passive workers, who might otherwise not fully utilize their capacity. This indicates that bundling can enhance workers' capacity usage and profit margins compared to the no-bundling scenario, robustly in all combinations of α and β.

5.6. Managerial insights

Based on experiments conducted, we derived the following managerial insights for practitioners who are interested in bundling tasks:

- The number of chargers provided to each worker during registration affects the scooter collection rate boosted by the bundling strategy. Too many chargers may raise operational costs, while too few limit workers' charging capacity, reducing the effectiveness of bundling. The bundling algorithm is more beneficial when the majority of workers have enough chargers, rather than allocating a small number of chargers to many workers. Providing enough chargers, even at some operational cost, is an essential first step to make the bundling algorithm work effectively with an unstable workforce.
- Our findings indicate that different λ in the PMB model result in varying outcomes. For practical applications, it is recommended to derive λ from workers' reservation data. Specifically, collect data on whether workers accepted a bundle based on the given reward, dispersion of scooters, and required travel distance. Use this data to determine the λ value that best aligns with the collection probability in the PMB framework, and adjust it as new data becomes available. During these adjustments, the VMB model can serve as a reliable alternative, as it delivers stable performance without requiring additional parameter tuning. Given its stability, we recommend deploying the VMB model as the initial bundling strategy on the platform and gradually transitioning to the PMB model as more data is collected and refined.
- The bundling policy is recommended when workers' participation in the platform is passive. Experiments show that the effectiveness of bundling is maximized when the number of workers is smaller rather than larger. Therefore, if the number of workers is sufficient to collect all scooters without bundling—for example, when the total charging capacity of all workers exceeds the total required battery charge of the scooters and the workers are relatively evenly distributed across the regions—bundling need not be applied initially. This avoids unnecessary computational effort and potential competition among workers. Conversely, in situations where these conditions are not met, applying bundling is expected to be more efficient. To implement this, it is recommended to divide the service time and regions, assess the number of workers actively available in each region at designated times, and determine whether to apply bundling based on the regional worker distribution.
- Regarding the *MaxBundleSize*, setting it too small may fail to generate sufficient synergy from bundling, resulting in minimal benefits. On the other hand, setting it too large may create bundles that exceed workers' capacity limits, rendering them impractical. To address this, it is deemed efficient to set *MaxBundleSize* based on the default number of chargers uniformly provided to workers during registration. While the actual number of chargers may vary depending on a worker's commitment or activity level, using this conservative baseline ensures that the bundles are applicable to the widest range of workers.

6. Conclusions

This study demonstrated the applicability of bundling models using domain-specific properties of the scooter-collecting industry through simulation experiments. The model incorporated gig workers' scooter collection behaviors to create synergies that entice workers. The proposed bundles effectively increased the collection rate compared to the no-bundling case, approaching the upper bound of the no-bundling case. The proposed PMB model showed superior performance with appropriate parameter settings, while the VMB model showed stable performance.

Numerical experiments show that bundles are highly attractive options beyond workers' activity quotas, encouraging greater engagement with the platform. This resulted in higher total collection rates and increased worker margins compared to the no-bundle cases. The scenario where the impact of bundling is most evident is when the workers' total capacity is just enough to cover the charging requirements of scooters. Also, when scooters are less clustered, bundles can effectively fill the distance gap by allowing workers to collect multiple distant scooters in one reservation. The effectiveness of the two-step bundling strategy, applicable to industries with an unstable workforce, was demonstrated by its comparable performance to the PI-NB model, which directly assigns tasks to workers. Accordingly, the proposed approach can be applied to gig economy-based operations where the platform needs centralized decision-making for decentralized workers.

The findings suggest the following managerial insights. Providing sufficient chargers during registration is essential to enhance collection rates and ensure the algorithm works effectively with an unstable workforce. Using the VMB model as a stable model first is recommended, with λ for the PMB model calibrated over time using workers' reservation data to enhance bundling performance. Finally, the bundling strategy should be implemented during specific periods based on each region's scooter distribution and worker capacity.

While the study establishes the efficacy of the bundling approach, the authors acknowledge that the calibration of bundling models requires further investigation. Specifically, the objective terms in the model of the VMB and the PMB models may benefit from refinement with real-world data on gig workers' behavior. Nevertheless, the study provides a promising foundation for boosting the operational efficiency of gig economy-based operations. Future research may involve exploring bundling algorithms for scenarios involving real-time task dynamics, including situations where scooter usage and charging occur simultaneously.

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Data availability statement

The data that support the findings of this study are available from the first author upon reasonable request.

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Appendix A. Pseudo-code for bundle generator algorithm

Algorithm 1 Near pack generator

Input: $\forall i \in N$, $MaxBundleSize \in \mathbb{R}$
Output: Set of candidate bundles B_{Near}

$B_{Near} \Leftarrow \emptyset$
for all $i \in N$ **do**
    $base \Leftarrow i, C \Leftarrow \emptyset$
    while $|C| < MaxBundleSize - 1$ **do**
        $t \Leftarrow nearestnodefrombase$
        $C \Leftarrow C \cup \{t\}$
        $base \Leftarrow t$
    end while
    $B_{Near} \Leftarrow B_{Near} \cup \{sub \cup \{i\} | \forall sub \subseteq C\}$
end for
return B_{Near}

Algorithm 2 Node pack generator

Input: $\forall i \in N$, $MaxBundleSize \in \mathbb{R}$
Output: Set of candidate bundles B_{Node}

$B_{Node} \Leftarrow \emptyset$
for all $i \in N$ **do**
    $C \Leftarrow MaxBundleSize - 1$ number of nearest node from i
    $B_{Node} \Leftarrow B_{Node} \cup \{sub \cup \{i\} | \forall sub \subseteq C\}$
end for
return B_{Node}

Algorithm 3 STD pack generator

Input: $\forall i \in N$, $MaxBundleSize \in \mathbb{R}$, distance matrix $D^{N \times N}$, predetermined distance $d \in \mathbb{R}$
Output: Set of candidate bundles B_{STD}

$B_{STD} \Leftarrow \emptyset$
for all $i \in N$ **do**
    $R \Leftarrow \{j \in N | D_{ij} \leq d\}$
    $C \Leftarrow \{i\}$
    while $|C| < MaxBundleSize - 1$ **do**
        for all $j \in R$ **do**
            $v_j \Leftarrow$ standard distance deviation of $C \cup \{j\}$
        end for
        $j' \leftarrow indexjofthesmallestv_j$
        $C \Leftarrow C \cup \{j'\}$
    end while
    $B_{STD} \Leftarrow B_{STD} \cup C$
end for
return B_{STD}

Appendix B. Additional constraints for PI-NB model

Two valid inequalities have been added. We define q_j^s of q_j values sorted in ascending order $(j \in N)$. For example, if $q_1 = 50, q_2 = 70, q_3 = 30$, then $q_1^s = 30, q_2^s = 50, q_3^s = 70$. Now, let c_c be the largest index of j when adding up q_j^s from the smallest j until the sum does not exceed $|K| * Q$, the sum of the collectible capacity of total workers. Then, c_c is the upper bound of the total collected scooters as shown in Constraint (B1).

$$c_c = \max\{j' \in N | \sum_{j=1}^{j'} q_j^s \leq |K| * Q\}$$

$$\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} z_{ij}^k \leq c_c + |K| \tag{B1}$$

Also, let p_j^s denote the sorted p_j values in ascending order. Then, let c_p be the smallest sum of the reward of the c_c number of scooters. The parameter r in Constraint (B2) is small enough so that the influence of c_p is less than 1, not disturbing the maximum number of collectible scooters.

$$c_p = \sum_{j=1}^{c_c} p_j^s$$

$$\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} (1 - r * p_j)\ z_{ij}^k \leq c_c + |K| - r * c_p \tag{B2}$$