A Gig Worker-Centric Approach for Efficient Picking and Delivery of Electric Scooters

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ABSTRACT

Electric scooter rental companies such as Bird and Lime rely on gig workers to recharge their scooters. This paper discusses some of the limitations of the compensation schemes of these companies and the processes that these companies utilize to pick and deliver electric scooters. These limitations are discussed from the perspective of a gig worker. In the proposed approach, gig workers provide their schedule, capacity, and travel requirements to the app, and the app then assigns the scooters (or delivery stations) to the gig workers. Two integer programming models, which minimize the overall effort necessary to collection and deliver scooters, are presented. Numeric experiments that show the potential productivity gains from the proposed approach over the existing approach are presented. The main objective of this research is to present analytical methods that can be utilized to increase the productivity of the system, reduce the revenue uncertainty of gig workers, and thus make the job of a charger more attractive.

KEYWORDS

Business Process Optimization, Compensation Mechanism, Gig Workers, Mechanism Design

1. INTRODUCTION

There has been a great increase in the use of smart phone app based electric scooter rental companies (Bird, 2021; Lime, 2021; Spin, 2021) in the US cities and other parts of the world. For instance, Bird, an electric scooter rental company, which was founded in year 2017, has reached more than 100 cities by the end of 2018 and received hundreds of millions of dollars in funding (Emerson, 2018). These electric scooters have potential to provide a great value to individuals, especially in urban areas, where pedestrian space is a big constraint. These scooters are small (smaller than bicycle) and have dock-less charging. Furthermore, they emit zero greenhouse gases and have almost zero noise pollution.

One of the unique aspects of the business model of these scooter companies is that they rely on gig workers to pick and deliver (return) their scooters. Anyone with a smartphone can become a contract-worker for these companies. One advantage of this gig-model is that the scooter rental companies do not have to hire full time workers to recharge their scooters. Gig workers can potentially earn more than \$1000 per month by working as a part time worker for these companies (Atlantic, 2018; Ridester, 2021). Figure 1 shows the electric scooters that are available for recharging in Charlotte, NC, USA at a point of time. This view of the app allows a worker to locate the available scooters in a region and learn about the reward (“bounty” in Bird terminology) available for charging them.

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Figure 1. A Bird app showing monetary rewards available for charging birds scooters in the city of Charlotte, NC, USA (Source: Bird app)

After a gig worker picks and charges a set of scooters, the app then suggests the worker to select a space from a set of predesignated spaces to deliver (return) the charged scooters. These spaces are called nest in the terminology of Bird company. Figure 2 shows how a worker can select (claim) a space to drop the charged scooters. Currently, the apps only allow workers to return the charged scooters between 4:00am to 7:00am as the demand for scooters is higher in the morning commute hours. Chargers can claim a nest by tapping “claim nest” in the app, which reserves a nest for a period of 30 minutes. If the charged scooters are not delivered at the claimed nest location within the 30 minutes of claiming, then the nest is “released” to all the chargers to claim, and it reappears on the map. A charger, in the current model, can only claim one nest at a time and a typical nest has a capacity of 3 scooters as shown in Figure 2.

Although the idea of utilizing gig workers in the electric scooter rental industry is revolutionary, the existing compensation, and scooter picking, and scooter delivery (return) mechanisms of these companies have several limitations that make them less attractive for their workers. From the perspective of a gig-worker, one of the fundamental limitations is that it causes a great uncertainty in the expected revenue of a charger from her scooter collection journey. For example, in the worst case it is possible that the charger may not get any revenue for her trip. This is possible because by the time she reaches an electric scooter there is a chance that some other worker can arrive at the location a little earlier and claim the scooter. Lorenz (2018) documents worker safety issues in case more than one worker arrive to claim a scooter at the same time. Lime beta tested a new reserve feature in a few cities that would allow workers to reserve a scooter for 30 minutes before beginning her scooter collection journey (Hawkins, A. J., 2019). While delivering the charged scooters to nests, the revenue uncertainty is lesser for workers compare to scooter picking phase, as the worker can reserve a nest for the next 30 minutes. This provides a level of guarantee that if a worker arrives at a nest on time (30 minutes), he will be able to return the scooter and get the monetary reward.

Three additional limitations of the scooter picking, and scooter delivery processes of these companies are presented below. These limitations are discussed from the perspective of a gig worker.

Figure 2. A Bird app displaying the available Nests (charging station) in Santa Monica city (Source: Bird app)

- 1.1 Inflexible Schedule Requirements for Workers:** A gig worker faces many schedule related restrictions. For example, in the “Scooter Picking Phase,” scooters either cannot be claimed in advance (as is the case with Bird scooter app) or if they can be claimed ahead of the journey (as is the case with “beta tested” feature of Lime), a scooter can be claimed for a fixed time (in this case for the next 30 minutes). In the “Scooter Delivery Phase,” the worker can only claim nests for a limited time frame from 4 am to 7 am. Note that typically a worker can only claim one nest at a time, which guarantees that she will have space to leave her charged scooters (up to 3 scooters) at the end of her journey.
- 1.2 Inefficient Utilization of Workers:** In the existing approach, the workers do not act in a coordinated manner. That is, each worker picks her own “picking” strategy independently. Therefore, the number of scooters that can be picked per hour is expected to be lower than what it would be if the workers act in a coordinated manner. That is, no two workers hunt for the same set of scooters at the same time. The proposed approach essentially avoids such situations. Later in the paper, numerical simulations are presented that compare the productivity of the existing approach with the proposed approach.
- 1.3 Work Safety Issue:** Conti (2019) points out the physical risks associated with the fact that the workers have to “hunt” for the same set of scooters in the existing business model of the scooter rental apps. This issue occurs if two or more gig workers arrive at the same scooter/s at almost the same time and try to claim the scooter/s.

The approach presented in this paper is a generalization of Lime’s beta tested approach (Hawkins, A. J., 2019) which allows workers to reserve a scooter before they start their scooter picking journey. In the proposed approach workers can specify their regions (area), capacities, and schedules to the app and the app then assigns the scooters to workers (or workers to nests). The app can make these

assignments several times a day and this information is made available to gig workers. For example, a worker can specify to the app that he can collect up to 20 scooters in a specific neighborhood (user defined) between 9am and 11am. The proposed mechanism, therefore, provides more functionalities and flexibility to gig workers than the existing approach. It, through the assistance of the app, increases the overall productivity of the workers and of the system by minimizing the efforts required to pick and deliver the scooters. This approach has several advantages for gig workers over the existing mechanism as it provides more flexibility, higher productivity (more efficient utilization of workers), and lower revenue uncertainty. The main objective of this research is to present analytical methods that can be utilized to increase the productivity of the system, decrease the revenue uncertainty of gig workers, and thus making the job of the charger more attractive.

The rest of the paper is organized as follows. In the section 2, the paper presents the literature review that is relevant to this research. The proposed approach along with the necessary integer programming models are presented in section 3. Section 4 presents the numerical experiments that shows the productivity gains from the proposed approach and computational times required to solve the proposed models by using CPLEX 12.9.0 for some problem instances. The last section of this paper presents the limitations of the proposed approach and discusses the conclusions of this paper along with some ideas for future research.

2. THE LITERATURE REVIEW

Electric scooter rental companies such as Bird, Lime, and Spin have started only a few of years ago in year 2017. There are some published patents about the design of electric scooters (Patmont, 1998), but unsurprisingly, most of the existing analysis of these companies and their market models are presented by freelance bloggers and news websites. This phenomenon has not received any attention of the Information Systems or Business Analytics community yet. This paper is the first academic research paper that formally analyzes some of the business processes of these companies and suggest alternative approaches.

There are several papers in Information Systems literature that have investigated the broader phenomena of Gig economy. Sundararajan (2013, 14) analyze Uber, Airbnb, car sharing in the gig economy context. Sundararajan (2016) presents an optimistic view about the role of gig workers over traditional employment. Zervas et. al. (2017) study the impact of Airbnb on the hotel industry. Burtch et. al. (2017) present an empirical examination of the gig-economy and entrepreneurial activity. Greenwood et. al. (2017) discuss a multidisciplinary research in the rapidly evolving gig-economy context. Greenwood and Wattal (2017) present an empirical investigation of ride sharing and alcohol related motor vehicle homicide. Huang et. al. (2018) study how local economic conditions impact worker participation in the online gig economy. Malhotra and Marshall (2014) and Weber (2014) present the myriad of problems such as moral hazard that exist in the context of sharing economy (gig economy).

Kevin (2019) discusses aspects of the electric scooter rental companies from the perspective of a charger. Stahl (2018) discusses different features (screens) of the electric scooter rental apps. The article also analyzes the expected earnings of workers under different level of workers' efforts. Ezra (2018) discusses the job of Bird charger and the process of becoming one. Gordon (2019) and Marshall (2019) present some challenges to the business models of these apps. They observe that some scooter companies have hired full time workers in place of Gig workers to fix its scooters in several cities, including San Diego, Dallas, and Austin.

There are two analytical models presented in the paper. The first model is for scooter picking phase, and the second model for scooter delivery phase. The first model is a generalization (a variation) of a well-known optimization problem called uncapacitated facility location problem (UFLP). In the version presented in this paper has the capacity related binary variables instead of continuous capacity variables. The UFLP has been extensively studied in the literature. This problem belongs

in the category of discrete facility location problems. Balinski and Wolf (1963) provide one of first formulation of the UFLP in the literature. In the UFLP, the decision maker finds the optimal placement of facilities of unrestricted capacities to n potential facility locations such that the cost (transportation and facility selection cost) of satisfying the demands of all the customers is minimized. Atta et. al. (2019) provide an overview of uncapacitated facility location problem and discuss several heuristic algorithms to solve the problem.

As this is the first research study that analyzes the business processes of the scooter rental companies, the focus of this paper is on exploring computationally easier models and to gain further understanding of the setting. As discussed in the future research section, it is possible to develop more sophisticated analytical tools for workers than what is proposed in the paper. For example, the app can possibly suggest optimum routes to workers rather than just optimum assignments. Construction of such models will lead to much more complex models such as generalized version of Multiple Traveling Salesman Problem (mTSP). mTSP is a generalization of the Traveling Salesman Problem (TSP) in which more than one salesman is allowed (Bektas, 2016). MTSPS (2021) provides a good overview of some common variations of Multiple Traveling Salesman problem. Such models are also closely related to a variant of Traveling Salesmen problem, called Vehicle Routing Problem. Laporte (1992) presents an overview of exact and approximate algorithms for Vehicle Routing Problem. Dutta et. al (2019) discuss a modified Kruskal's algorithm to improve genetic search for open Vehicle Routing Problem.

3. THE PROPOSED APPROACH

There are two phases in the proposed approach. These two phases correspond to the two phases of the business models of the scooter rental companies. In the first phase, the available scooters are optimally assigned to the available workers. The requirements of the workers and their locations are used to make the optimum assignments. Moreover, the model allows a way for the app to control the number of workers that must be selected during the scooter collection phase. The number of times the app should assign scooters to workers will depend on the city and the number of scooters and workers that are available in the city. Although the question of finding the number of times scooters should get distributed to charger is important in our setting, it is not the focus of this research. The models presented next consider one of the times when the app must assign the workers to the scooters (or the workers to the nests).

Below are the notations for the integer programs for the two phases of the proposed approach. We will first discuss the model for the picking phase and then for the scooter delivery (return) phase:

i : The index of scooter i .

j : The index of worker j .

I: The set contains the indexes of the available scooters.

J : The set contains the indexes of the available workers.

K_j : The number of scooters that individual j would like to charge in the timeslot (worker capacity).

L_j : The minimum number of scooters that worker j is allowed to collect in the timeslot. This parameter can be defined by the app for some workers (optional) to ensure that at least a certain number of workers must be selected. This parameter may take the same value for all the workers, or the app can use the worker quality parameter (Q_j , given below) to determine this for the workers. If the app determines L_j based on Q_j , then a lower Q_j for a worker would mean higher L_j value. This is because those workers who have higher quality scores (lower Q_j values) must be picked first.

Q_j : The quality score of worker j . In this paper, Q_j is between 1 and 10. The highest quality score of worker corresponds to $Q_j = 1$ and $Q_j = 10$ corresponds to the quality score of the lowest quality worker. The app can use the data including workers efficiency, and punctuality to determine a worker's quality score. A quality score of 1 can be initially given to all workers. Q_j . This score is used in the objective function of the proposed models to incentivize selection of higher quality (lower Q_j) workers.

E_{ij} denotes the effort required by individual j to pick (and charge) scooter i . Note that this information is assumed to be given to the app in this paper. Factors such as the distance between a charger and a scooter can be used to determine the effort necessary to collect a scooter by a worker. One of the fundamental differences between the existing reward policy of the scooter rental companies and the proposed approach is that in the existing policy, the reward obtained in exchange for charging a scooter is a function of only i (scooter characteristics). For example, there may be only three possible reward values \$5, \$12, and \$20 depending on the city of a gig worker. In the proposed approach, however, the reward is based on both i and j (scooter and worker characteristics). Although the issue of finding the right reward for a given effort for the charger is important and related to the research of this paper, this paper does not focus on this issue. Instead, the focus of this research is to design mechanisms for finding the optimum assignments of the workers to the scooters (or the scooters to the nests). The overall objective of the mechanisms of this paper is to minimize the total effort (plus the sum of quality score in model P) required by the chargers to pick (or deliver) the scooters.

Integer Programming Model for the Scooter Picking Phase:

Before the app uses the model given below, it removes the scooters, which cannot be reached by any worker. That is, scooters that are outside the geographic range to all the workers. This ensures that all the available scooters can be assigned to at least one worker.

Decision variables:

$x_{ij} = 1$ if scooter i is assigned to worker j

$= 0$, otherwise

$z_j = 1$ if worker j is chosen

$= 0$, otherwise

Below is the integer programming model that the app can use to find the optimum assignment of the scooters to the workers:

$$\mathbf{P:} \text{ Min } \sum_{i \in I} \sum_{j \in J} E_{ij} x_{ij} + \sum_{j \in J} Q_j z_j$$

$$\sum_{j \in J} x_{ij} = 1 \quad \forall i \in I$$

$$\sum_{i \in I} x_{ij} \leq |I| z_j \quad \forall j \in J$$

$$\sum_{i \in I} x_{ij} \leq K_j \quad \forall j \in J$$

$$\sum_{i \in I} x_{ij} \geq L_j z_j \quad \forall j \in J$$

$$x_{ij}, z_j \in \{0, 1\} \quad \forall i \in I, j \in J$$

The objective function of the above formulation minimizes the sum of the total effort (cost) of collecting the available scooters (III) and a quality score of the selected workers. The first set of constraints ensure that each scooter must be assigned to 1 worker. Note that even if a scooter is assigned to a worker, it does not mean it will eventually be picked by the worker. The second set of constraints ensures that if worker j is not selected ($z_j = 0$), then $x_{ij} = 0, \forall i \in I$. The third set of constraints ensures that the workers can be assigned as many scooters as their capacities (K_j). The fourth set of constraints ensures that at least L_j scooters must be assigned to worker j , if the worker j is selected. This set of constraints are optional. This set of constraints also would also allow the app to control the number of works that must be selected. For example, if the app would like to have at least s number of workers, then it can replace the (L_j, z_j) by L_j for the workers with the top s Q_j values (lowest Q_j values). This will ensure that at least s workers are selected. The above model performs computationally more efficiently than other models with an additional constrain: $\sum_{j \in J} z_j \leq s$

in the above formulation (this has been tested by solving the model by using CPLEX studio). The fifth set of constraints ensures that all the decision variables are binary.

Observation 1: The formulation P is a variation of uncapacitated facility location problem. The above formulation's objective function, and 1st, 2nd, and 5th set of constraints exist in uncapacitated facility location formulation as well.

After the scooter picking phase, the workers charge the collected scooter. After the scooters are charged, the website collects the data about the number of scooters that each worker has charged and ready to drop before beginning the "delivery phase."

Integer Programming Model for the Scooter Delivery Phase:

T_j : the number of scooters that are ready to be delivered by worker j .

k : the index of nest k .

K : The set contains the indexes of the available nests.

N_k : the scooters capacity of nest k .

Decision variables for this phase:

$x_{jk} = 1$, if worker j is assigned to nest k .

$=0$, otherwise.

y_{jk} : the number of scooters to be dropped by worker j to nest k .

$$Q: \text{Min } \sum_{j \in J} \sum_{k \in K} Q_j E_{jk} x_{jk}$$

$$\sum_{k \in K} y_{jk} = T_j \quad \forall j \in J$$

$$\sum_{j \in J} y_{jk} \leq N_k \quad \forall k \in K$$

$$y_{jk} \leq T_j x_{jk} \quad \forall j \in J, k \in K$$

$$x_{jk} \in \{0, 1\}, y_{jk} \in Z^+ \quad \forall j \in J, k \in K$$

In the above formulation, the objective function minimizes the total effort needed to deliver (return) all the charged scooters. The first set of constraints ensures that each worker must be given

enough capacity in different nests that is sufficient to drop all her charged scooters (T_j). The second set of constraints ensures that each nest receives no more scooters than its capacity (N_k). The third set of constraints ensures that if a nest is not selected by a worker, then that worker must not drop any scooters to that nest. In case a nest is selected by a worker, the third set of constraints also ensures that the worker can drop as many scooters as his capacity. The last set of constraints ensures that all the x_{jk} variables are binary and y_{jk} variables are nonnegative integer.

The proposed reward scheme has several advantages over the existing reward schemes of the apps. In the proposed scheme, the individual chargers are assigned to the electric scooters by the app. So, the charger is guaranteed the reward of charging a scooter if the charger claims the scooter (in the required timeframe). This approach allows the rental companies to improve the overall productivity of the system by using the resources (effort of the chargers) in a more effective manner, while reducing the revenue uncertainty experienced by the gig workers in this setting. That is, workers in the proposed approach do not hunt for the same set of scooters and they know the scooters they “should” pick (or deliver) before they begin their picking (or delivery) journeys.

4. NUMERICAL ANALYSIS

The computational efficiency of the proposed approach, in terms of computational time, is analyzed below. For this, the time required to solve problem instance of various realistic sizes are analyzed. Various problem sizes of model (P and Q) are formulated by using Optimization Programming Language (OPL) and solved by IBM CPLEX 12.9.0 on a laptop that has Intel (R) Core i5 processor and 8GB RAM. The model P is solved for problem instances, where $|I|$ (number of scooters) takes 200, 1000, and 3000 values and $|J|$ (number of workers) takes 10, 25, 50, and 100. Note that it is realistic because we do not expect more than 3000 scooters in a city from one rental company. The model Q is solved for problem instances where $|J|$ (number of workers) takes 200, 400, 800 values and $|K|$ (number of nests) 10, 25, 50, 100. For simplicity, we assume $Q_j = 1$, $E_{jk} = 10$, $L_j = 0$, $T_j = K_j = |I|/|J|$, and $N_k = 3 \forall j, k$ in each scenario. E_{ij} for all i and j are calculated by using CD subroutine described later in this section.

To analyze the performance of the proposed approach, an imaginary grid of length (l) equals 100, and width equals 100, is created. To create five scenarios, the length and width of the grid is sequentially decreased to 80, 60, 40, and 20, and different number of workers are placed at the random coordinates of the grid. In each scenario, the scooters are placed at the random coordinates between 25 and 75. The purpose of creating these scenarios is to show how the productivity gain (in terms of the total distance traveled to collect all the scooters of the scenario) changes as the density of workers increases in a region. Note that E_{ij} values for model P are derived based on the original grid of length and width equal 100 by using CD subroutine.

The pseudocodes of Scooter Picking (SP) algorithm and Coordinate to Distance (CD) subroutine are presented next. These algorithms are utilized to measure the distance traveled by the workers in different scenarios without the optimization models. The CD subroutine takes the coordinates, of the scooters and the workers for instance, and returns the distance matrix ($A(i, j)$). This matrix captures the distance between pairs of scooters and workers (or workers and nests). The SP algorithm uses a greedy approach to assign the workers to pick the scooters, as expected in a real-world situation. That is, a worker starts the journey by picking the scooter that is closest to her. If by the time the worker arrives at the chosen scooter's location and does not find it, then she again searches for the scooter closest to her. The algorithm assigns the workers to the available scooters till there are available scooters, or the workers have available capacity to pick scooters. For simplicity of this analysis, the workers travel directly to the scooters (or nests) in Euclidean space for picking of scooters. In the first

step of the SP algorithm, the distance between all the pairs of workers and scooters are calculated by utilizing the CD subroutine. In the second step, the scooter closest to each worker is identified. In the third step, the distance of the worker closest to each scooter is calculated. In the fourth step, the coordinates of workers are recalculated depending on the relative position of the worker and the scooter closest to the worker. In the fifth step if a worker is at the location of a scooter, then the scooter is picked, and the worker's pick capacity is decreased by one and the scooter is removed from the available scooters. In the next two steps, the distance and capacity values of workers are recalculated. If there is no unused capacity left for a worker, then the worker is removed from the available set of workers. The algorithm runs till there are available scooters or workers.

Subroutine: Coordinate to Distance (CD)

Input: X_s (contains x coordinates of Scooters), X_w (contains x coordinates of Workers), Y_s (contains y coordinates of Scooters), Y_w (contains y coordinates of Workers)

Output: Matrix A (i, j), where (i, j) is distance between i and j .

For $i = 1$ to $|I|$ and $j = 1$ to $|J|$

$$D(i, j) = \sqrt{(X_s[i] - X_w[j])^2 + (Y_s[i] - Y_w[j])^2}$$

Return $D(i, j) \forall i \in I, j \in J$.

Algorithm: Scooter Picking (SP)

Input: $X_s, Y_s, X_w, Y_w, K_w^f, D=0$

Find the distance between each pair of worker and scooter by using CD subroutine: $D(s, w) \forall s \in I, w \in J$.

Find the scooter closest to each worker, $S_w = \arg(s) \text{ Min } D(s, w) \forall w \in J$

Calculate the distance, $d = \text{Min } D(s, w) \forall s \in I, w \in J$

Recalculate the coordinates of workers:

IF $((x_s - x_w) > 0 \text{ and } (y_s - y_w) > 0)$

$$x_w \leftarrow x_w + \frac{|(x_s - x_w)|d}{\sqrt{(x_s - x_w)^2 + (y_s - y_w)^2}}; y_w \leftarrow y_w + \frac{|(y_s - y_w)|d}{\sqrt{(x_s - x_w)^2 + (y_s - y_w)^2}}$$

$\forall s \in S_w, w \in J$.

IF $((x_s - x_w) > 0 \text{ and } (y_s - y_w) < 0)$

$$x_w \leftarrow x_w + \frac{|(x_s - x_w)|d}{\sqrt{(x_s - x_w)^2 + (y_s - y_w)^2}}; y_w \leftarrow y_w - \frac{|(y_s - y_w)|d}{\sqrt{(x_s - x_w)^2 + (y_s - y_w)^2}}$$

$\forall s \in S_w, w \in J$.

IF $((x_s - x_w) < 0 \text{ and } (y_s - y_w) > 0)$

$$x_w \leftarrow x_w - \frac{\left| \left(x_s - x_w \right) \right| d}{\sqrt{\left(x_s - x_w \right)^2 + \left(y_s - y_w \right)^2}}; y_w \leftarrow y_w + \frac{\left| \left(y_s - y_w \right) \right| d}{\sqrt{\left(x_s - x_w \right)^2 + \left(y_s - y_w \right)^2}}$$

$\forall s \in S_w, w \in J.$

IF $\left(\left(x_s - x_w \right) < 0 \text{ and } \left(y_s - y_w \right) < 0 \right)$

$$x_w \leftarrow x_w - \frac{\left| \left(x_s - x_w \right) \right| d}{\sqrt{\left(x_s - x_w \right)^2 + \left(y_s - y_w \right)^2}}; y_w \leftarrow y_w - \frac{\left| \left(y_s - y_w \right) \right| d}{\sqrt{\left(x_s - x_w \right)^2 + \left(y_s - y_w \right)^2}}$$

$\forall s \in S_w, w \in J.$

IF $x_s = x_w, K_w = K_w - 1 \forall s \in S_w, w \in J, D = D + dII, I \leftarrow I/w.$

If $K_w = 0, X_w \leftarrow X_w / x_w, Y_w \leftarrow Y_w / y_w,$

$X_s \leftarrow X_s / i_s, Y_s \leftarrow Y_s / j_s \quad s \in S_w.$

If $|X_w| > 0$ and $|X_s| > 0$, Go to step 1.

return D.

All the problem instances described initially in this section can be solved within 1 minute for model P. Table 1 provides the time required to solve the model Q for different problem sizes (based on the number of workers (|J|) and the number of nests (|K|)) in seconds. As Table 1 shows, the optimizations model Q of this paper can be efficiently solved for realistic problem sizes of this setting.

Table 1. Computational times (in seconds) for different problem instances of model Q

(J)	K =10	K =25	K =50	K =100
200	0.01	0.55	3.4	46
400	0.01	0.98	27	55.84
800	0.02	1.07	32.8	192

The numeric experiments that are designed to show the productivity gains from the proposed approach are presented next. For demonstration purposes, the problem instances of a variety of |I| and |J| values, were created for the scooter picking phase. Similar analysis can be done for scooter delivery phase, although it is not presented in this paper. To measure the productivity gains from the proposed approach, first the scooter assignment model (P) is implemented to find the optimum assignment of the workers to the scooters and then the SP algorithm with CD subroutine is utilized to find the routes (sequence) for the workers, and to calculate the total distance travelled in the different scenarios. To simulate the existing approach, the SP algorithm with CD subroutine is utilized without using the model (P). Table 2 shows the productivity gains (in fraction) from the use of the proposed approach in different scenarios. That is, the difference in the performance (the total distance traveled to collect all the scooters) with or without the implementation of the proposed model (P).

Table 2. Productivity gains from the proposed approach under different scenarios based on the density of workers.

III	I,JI	1 ($l=20$)	2 ($l=40$)	3 ($l=60$)	4 ($l=80$)	5 ($l=100$)
200	10	0.04	0.02	0.00	0.00	0.00
200	25	0.07	0.03	0.01	0.00	0.00
200	50	0.10	0.05	0.02	0.01	0.00
200	100	0.14	0.09	0.05	0.03	0.00
400	10	0.05	0.02	0.01	0.00	0.00
400	25	0.09	0.04	0.01	0.00	0.00
400	50	0.12	0.07	0.03	0.01	0.00
400	100	0.17	0.11	0.07	0.04	0.01
800	10	0.07	0.03	0.01	0.00	0.00
800	25	0.12	0.05	0.02	0.00	0.00
800	50	0.16	0.09	0.04	0.02	0.00
800	100	0.21	0.14	0.09	0.05	0.02

As shown in Table 2, the productivity gains are higher (given in fraction) in the scenarios where the density of gig workers are higher. That is, if the density of workers in a scenario increases then the proposed approach outperforms the existing approach. However, if the workers are sparsely located then there may not be any performance gain from the proposed approach. As shown in Table 2, the maximum possible productivity gain observed across scenarios was around 21%. This shows that by utilizing the workers in a coordinated manner, the scooter rental apps can potentially enhance the overall productivity of the system. Moreover, it can reduce the revenue uncertainty of workers because they know the expected revenue from their scooter picking (or delivery) journey before they begin it.

5. THE CONCLUSIONS, LIMITATIONS, AND THE FUTURE RESEARCH

This paper discusses some of the limitations of the compensation mechanisms of the electric scooter rental companies from the perspective of gig workers. It is shown that by gathering the requirements of gig workers (schedule, travel, and capacity) and utilizing it in the proposed optimization model, the rental apps can improve the overall productivity of workers in the scooter picking and delivery processes. The objective of the proposed approach is to increase the attractiveness of the job of gig workers by making their jobs more productive and by reducing their revenue uncertainty and risk. This approach utilizes analytical models that use workers and apps inputs in deciding the optimal assignments of scooters to workers or workers to nests. The proposed approach suggests that the app should provide the “picking strategy” for workers. In the existing approach, each worker “hunt” independently for their scooters or nests.

It is shown that the optimization problems associated with the scooter picking process is a variation of uncapacitated facility location problem. Through numerical experiments, it is shown that the models proposed in the paper can be efficiently solved for the size problems that exist in this setting. The paper also shows that by utilizing the workers in a coordinated manner, the scooter rental apps can enhance the overall productivity of the system (gig workers). This approach also reduces the revenue uncertainty of workers in this environment because they know the expected revenue from a scooter picking (or delivery) journey before they the start of the journey.

One of the main limitations of the proposed approach from the e-scooter rental company’s standpoint is related to the resource required to develop and implement the approach. The existing

approach, on the other hand, is simpler for the app companies and does not require development of any additional analytics. Moreover, there are other worthwhile projects that these companies can pursue to achieve higher value for the company at this time, other than building more analytical capabilities for its (gig workers), which is the objective of this paper. For example, the company can take different set of actions from the customers perspective to add value to the business. For instance, the business can optimize the availability of scooters to the right nests so that the customers get the scooters as efficiently as possible. That is, the companies can take actions to ensure enough scooters are available to the right customers at the right time. However, the focus of this research work is on the gig-workers rather than the customers.

In the future, this research can be extended adding more complex optimization models which can recommend optimum routes for each gig-worker (for scooter picking and delivery) rather than the simpler facility location model models that are presented in this paper can be proposed. Initial exploration of this research leads to the fact that finding the optimum routes for gig workers in this setting would require solving problems that are generalization of Vehicle Routing problem. One contribution in this direction could be to develop new heuristics for the new formulations of this setting. In addition, models that optimize the processes from the perspective of customers, rather than just the gig workers, can be considered in a future research.

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