Delivery Zones Partitioning Considering Workload Balance Using Clustering Algorithm

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Abstract: This research proposes a novel approach for partitioning delivery zones in Bangkok that utilizes a combination of clustering and iterative algorithms. The approach leverages 30 days of delivery data to create delivery zones that having balanced workloads for drivers. The study begins by analyzing the delivery data to confirm the presence of unbalanced workloads across drivers within the 30-day period. To solve this imbalance, we use iterative k-means to adjust delivery zones considering the number of deliveries within the zone. The effectiveness of the approach was evaluated using two sets of parameters: geographic coordinates (latitude and longitude) and actual travel distance to reflect real-world scenarios. Regardless of the parameter set used, the experiments yielded balanced transportation areas with evenly distributed workloads. This approach demonstrates an improvement in workload equality compared to the original workload distribution.

1 INTRODUCTION

In recent years, the expansion of e-commerce has significantly increase the demand for delivery services, particularly in urban areas. This growth translates to a substantial daily volume of orders for both delivery and product pick-up, subsequently elevating the operational costs for delivery companies. This essential process, known as last-mile logistics, faces significant challenges in urban environments. These challenges include traffic congestion, unique road networks constraints. Additionally, customer-related limitations, such as limited operating hours of delivery locations and the availability of the drivers, add further complexity to the process.

Driver assignment plays an important role in enhancing operational efficiency. The establishment of delivery zones fundamental for both drivers and route planners, aiding in the organization of last mile logistics. A driver's familiarity with an area significantly influences customer satisfaction; this includes not just navigating skills, but also an understanding of the specific delivery protocols at customer locations.
Efficient route planning can reduce a company's transportation costs and contribute to alleviating environmental concerns. In addition, maintaining consistent delivery zones provides planner with an advantage, especially when faced with tight decision making timelines, such as executing time-sensitive delivery.

There are several strategies for generating delivery zones, including the use of modern optimization algorithms or the development of machine learning models. In 2022 and 2023, a combination algorithm based on k-means clustering was utilized (S.H. Huanga, 2023) (El Ouadi et al., 2022). Creating delivery zones ensuring an equitable distribution of workload requires the consideration of multiple factors, such as the total number of delivery destinations, the specific delivery time frames assigned to each location. Although clustering algorithms offer a methodology for dividing areas, they often fall short due to the potential for unbalanced clusters. Thus, this project introduces a two-phase approach that combines the strengths of clustering algorithm with iterative methods to establish zones that boast balanced workloads. This method utilizes a month's delivery data for generating equitable zoning strategy.

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2 LITERATURE REVIEW

Research focusing on route optimization for urban logistics often centers around the Vehicle Routing Problem (VRP), a pivotal challenge due to the VRP's classification as NP-hard. This complexity means that managing deliveries in urban areas involves navigating an exceptionally large decision space, making the efficient resolution of VRP crucial for effective logistics operations.

Recent trends in last-mile logistics research have shifted towards improving algorithms for finding efficient solutions in a short period of computational timeframe. However, an emerging trends involves leveraging artificial intelligence to tackle the problem. (Demir et al., 2022) is suggested that AI has the potential to significantly reduce the time complexity of creating delivery routes, particularly when dealing with large volumes of orders. Partitioning the city into zones is a crucial preliminary step in this process, as it can create time efficient solutions when generating vehicle routes.

The method of zoning prior to routing has gained popularity in managing last-mile logistics, as highlight by research presented by (Muhammad et al., 2023) and (Zhao et al., 2022). The implementation of the zoning-based pricing strategies for the VRP has demonstrated effective performance (Shi et al., 2023), (Afsar et al., 2021). The research exhibits the importance of zoning in logistic operations, particularly in the context of last-mile delivery challenges.

K-means is a technique widely utilized in several VRP research, especially when dealing with zoning. K-means groups data points into distinct, non-overlapping clusters based on certain parameters (Hartigan, 1975). This method calculates distances between points and updates cluster centers, thereby effectively assigning data points to the most suitable cluster. The process utilizes a specific formula to determine the distance metric for this purpose. Although K-means clustering is applied across a broad range of fields due to its versatility, it is not without limitations. One notable drawback is that it is less likely that the number of data points in every cluster would be balanced, indicating a potential bias workload when assigning areas to drivers.

K-means has found successful application in other domains, particularly in zoning purposes. (Pedersen et al., 2022) implemented a weighted K-means method to effectively partition delivery zones specifically designed for drone logistics. Further relevant research includes the introduction of a Clustering-based Routing Heuristic (CRH) (Prajapati et al., 2023), aimed at optimizing last-mile logistics for a fresh food company. (Bruni et al., 2023) investigated the integration of machine learning with heuristic algorithms to address similar logistic challenges. (Ouadi et al., 2020) and (El Ouadi et al., 2022) combined K-means with time series methods to forecast demand, facilitating more effective zoning in urban areas.

The significance of zoning for effective workload planning has been emphasized by the recent research (Jabbari et al., 2020). (Wang et al., 2022) emphasize the need to consider driver workload would sustain morale within the courier workforce. Workload balance emerges prominently in numerous studies focused on last-mile logistics management, as shown in (S.H. Huanga, 2023). Further contributing to this discussion, (Lorenzo-Espejo et al., 2023) reveals a significant link between driver workload, their performance, and the distances they travel. (LI et al., 2022) employ K-mean to achieve balanced customer groups, showcasing the utility of machine learning techniques for creating balanced workload.

Recently, a study conducted by (Moreno-Saavedra et al., 2024) showcases a multi-algorithm approach that combines recursive and evolutionary algorithms with K-means. This approach aims to optimize the balancing of operational workload for drivers within the last-mile urban delivery system. This research highlights the significant advantages of integrating K-means with other algorithms to derive optimal solutions for logistical challenges. This integration not only enhances the efficiency of workload distribution among drivers but also contributes to the broader objective of improving the overall performance of last-mile delivery operations.

As shown in the literature, clustering algorithms are commonly used to generate zones for drivers. Workload balance is also a major focus in several research studies. However, many approaches address the problem on a day-to-day basis, where the driver's zone may change depending on daily delivery demands. On the other hand, our research utilizes a month's worth of data to create delivery zone, ensuring driver familiarity to the delivery areas. This provides a distinctive feature for our research.

3 METHODOLOGY

3.1 Data Information

This subsection focuses on a delivery dataset spanning one month, comprising 30,055 rows of delivery points. There are several columns providing delivery information such as driver id, delivery date, actual delivery time, and geometric coordinates. The first row for each driver on each day represents their depot location, and workload of each driver is then measured by considering the total delivery time and the number of delivery points.

3.2 Partition Algorithm

This subsection presents a novel algorithm that combines k-mean with an iterative approach, structured as a two-phase process. The initial phase employs k-mean to partition the urban area into distinct delivery zones. The second phase of the algorithm takes into account the distribution of deliveries within each zone, as determined in the first phase, to achieve workload balance across zones. The workload balance process is attained thought the use of a statistical method, which iteratively adjusts the allocation of delivery points to ensure that the delivery workload is evenly distributed.

```
Data: geographic coordinate, a number of
      drivers
Result: area of delivery
Initial step: assign delivery point to area of
  delivery using K-mean clustering according
  to the number of drivers;
calculate quartiles from the number of
  delivery;
Q1 ← the first quartile of clusters;
Q3 ← the third quartile of clusters;
; /* classification type of clusters
  */
for cluster ← the number of clusters do
    if the number of point in the cluster more
      than Q3 then
        Over-Zone ← cluster;
    end
    if the number of point in the cluster lower
      than Q1 then
        Under-Zone ← cluster;
    else
        Balanced_Zone ← cluster;
    end
end
```

Algorithm 1: Overall of classification clusters algorithm.

Algorithm 1 outlines the initial phase of the workload balancing procedure. This initial phase starts with the importation of delivery data, including the geographical coordinates of customers. These coordinates served as input for the clustering algorithm. The number of clusters is set to match the number of active drivers within the observed month. Utilizing k-means, each delivery point is allocated to a specific cluster based on proximity. Following the clustering process, the algorithm proceeds to calculate the first and third quartiles. The first and third quartiles calculated from the initial phase are retained and used as zone balancing criteria. Therefore, the algorithm consistently uses Q1 and Q3 from the first clustering step for every iteration. Each cluster is then classified into three categories:

1. Over-zone is the zone having delivery points more than Q3.
2. Under-zone is the zone having delivery points less than Q1.
3. Balanced zone is the zone having delivery points between Q1 and Q3.

```
Data: geographic coordinate, list of
      Over-Zone, list of Under-Zone,Q1,Q3
Result: area of delivery
while OverZone and UnderZone is not empty
 do
    num_over ← the numbers of clusters of
      Over-zone cluster;
    num_under ← the numbers of clusters of
      Under-zone cluster;
    adjusted_num_under ← add the number
      of points of Under-zone and divided by
      Q3;
    different ← a round up of
      adjusted_num_under;
    if Over-Zone is not empty then
        num_cluster ← num_over +
          (num_under - different);
        assign all delivery points in all
          Over-Zone to area of delivery using
          K-mean according to num_cluster ;
    end
    if Under-Zone is not empty then
        num_cluster ← different;
        assign all delivery point in all
          Under-Zone to area of delivery using
          K-mean according to num_cluster ;
    end
    classification new clusters in Over-Zone,
      Under-Zone and Balanced_Zone;
end
```

Algorithm 2: Overall of re-clustering algorithm.

In the subsequent phase of the workload balancing process, as detailed in Algorithm 2, the focus shift to the over-zone and the under-zone. For these two zones, k-means is repeatedly applied to refine the cluster until we have balanced workload.

The re-clustering strategy, designed to tackle the challenge of a limited number of drivers, on the principle of adjusting the number of zones to achieve a more balanced distribution of workload. Specifically, this approach seeks to decrease the number of zones classified under the under-zone category while increasing the number of zones classified as over-zone. In the final step of the process, clusters that have not yet achieved balance are subject to re-clustering, with the new number of clusters being determined as per calculations made in the previous step. After re-clustering, the balanced of each zone is again determined by the number of tasks and the quartile values which retrieve from the initial step. Finally, all the areas are re-examined to confirm that no zone is entirely encompassed by another. If there are zones to be intersect or be nested within each other, a further round of re-clustering is initiated. The number of cluster in this round corresponds exactly to the total number of intersecting zones.

3.3 Scenario with Actual Travel Distance

To craft zoning reflects real-world logistics, it is essential to consider the distances between delivery points. However, calculating all pairwise distances, especially for a large dataset, can be computationally expensive. For instance, utilizing a mapping service like Longdo Map API for this purpose would result in an operational that could take more than an hour given the size of the problem at hand. This approach is not feasible due to the high computational cost and excessive the time requirement. To dealing with this issue and enhance algorithm efficiency, instead of using all delivery points, we employ representative point strategy. This method selects a subset of points that effectively represent the broader set of delivery locations within a 500-meter radius. We assume that the 500-meter is a short distance that is negligible enough not to significantly impact travel time. This approach reduces the number of necessary API calls for distance calculation, improves the computation time of the zoning process. By focusing on representative points rather than the entire dataset, the computational burden is lessen without sacrificing the accuracy needed for practical route planning. However to accommodate this approach, there is a need to transition from a standard k-mean algorithm to a weighted k-mean variant (Kerdprasop et al., 2005). The weighted k-mean algorithm adjusts for the density of these representative points, ensuring that the clustering process accounts for the varying importance or frequency of deliveries within certain areas.

4 RESULTS

4.1 Overview of the Experiment

4.1.1 Data Overview

The investigation of the dataset reveals insights into the delivery operations of a real-world scenario over a one-month period. A total of 912 delivery trips were recorded during this timeframe, which translates to an average of approximately 30.4 drivers being dispatched daily to handle deliveries. Further analysis of the 30,055 delivery point records indicates that a significant majority, 26,669 rows, correspond to deliveries made on weekdays. This distribution suggests that the bulk of delivery operations are concentrated on weekdays, reflecting typical business operations and customer ordering patterns. On the other hand, 1,562 points are attributed to weekend deliveries. Notably, these weekend deliveries do not include depot assignments, which might imply a different logistical setup or operational protocol for weekend delivery services compared to weekdays. This breakdown of delivery data offers valuable insights into the operational dynamics and scheduling preferences.

The detailed analysis of weekday delivery operations reveals that the average number of active drivers per day stands at 33.14, with a relatively low standard deviation of 1.06. This indicates a consistent level of driver deployment on weekdays, demonstrating a stable demand for delivery services and effective workforce management. The range of active drivers, which spans from a minimum of 31 to a maximum of 35 drivers, further underscores this consistency, suggesting that operational needs and capacity are well-matched on a day-to-day basis. The median of the number of driver is at 33, indicating that the central tendency of driver deployment aligns closely with the average. This support the decision to utilize 33 as the target number of clusters for the subsequent zoning process.

4.1.2 Measurement for Drivers Workload

This section focuses on measuring driver workload. We consider both delivery time and the number of delivery points per driver. Table 1 presents selected statistics on driver workloads in term of delivery point and working time, split into weekend and weekday categories.

The data presented in Tables 1 highlights a substantial disparity in the workload between weekdays and weekends. This shows that the majority of the operational demands encounter during the weekdays. Specifically, the number of delivery points during

Table 1: Selected descriptive statistics of delivery point (pt) and working time (min) in a month on driver workloads split into weekday and weekend.

	Weekend		Weekday	
	pt	min	pt	min
average	33.28	19.23	867.429	431.30
Q2	36	13.06	925	511
SD	17.38	19.33	382.22	171.72
minimum	1	3	2	50
maximum	67	210	1880	736

weekdays is observed to be more than 26 times higher than those recorded over the weekends. Similarly, the total delivery time—or working hours—accumulated on weekdays surpasses that of weekends by approximately 20 times. With the substantially higher demands on weekdays, it is clear that zoning efforts should primarily focus on weekday data. Furthermore, the variation in workload—reflected in both the delivery time and the number of delivery points—suggests that relying on average values might not provide the most accurate representation of a typical driver's day. The median offers a more suitable metric for understanding and planning workloads.

Statistics from Table 1 reveals imbalances in driver workload, as evidenced by the standard deviation as well as maximum and minimum deliveries per driver per day. These disparities indicates a need for more equitable allocation of deliveries.

4.2 Clustering Result Using Geographic Coordinate

Figure 1 illustrates delivery points plotted over the map of the Bangkok metropolitan area, derived from one-month of delivery data.

Figure 2 illustrates the initial zoning generated by the first-phase algorithm. The lines encompass delivery areas into distinct zones by k-means algorithm whose number of clusters was determined as outlined in Section 4.1.1.

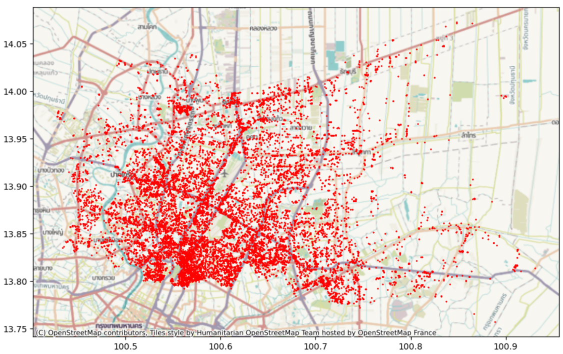

Figure 1: Original delivery points on the map.

Table 2: The quartile of delivery point in each clusters from first clustering.

Quartile	Delivery points in clusters (points)
minimum	80
Q1	436
Q2	588
Q3	1198
maximum	2114

Figure 2: The clusters of delivery zone from first K-mean clustering.

Table 2 displays the results of the quartile analysis performed on the list of clusters. When these results are compared with the initial data from weekdays, both the minimum and the median values of delivery points per cluster have increased, indicating a shift in workload distribution. However, the result shows that the maximum number of delivery points within a single cluster has surpassed even the original maximum value. This suggests that, despite efforts to redistribute the workload, imbalances still persist with some clusters being overloaded compared to others as shown in Table 3.

Figure 3 showcases a line graph that effectively compares the number of delivery points per area at different stages of the algorithm's application. On the graph, the X-axis categorizes areas in ascending order based on the number of delivery points they contain, from the fewest to the most. The Y-axis, meanwhile, quantifies the number of delivery points attributed to each area. The result shows the impact of the re-clustering algorithm, illustrating a trend toward a more balanced distribution of delivery points across

Table 3: Clusters from the initial clustering into three types.

Type of Zone	The number of Zone
Balance	17
Over	9
Under	9

cluster. At the initial stage, the graph shows significant variability in the number of delivery points per area. After two rounds of re-clustering attempts, the variability diminishes, reflecting a progressive equalization of workloads across different areas.

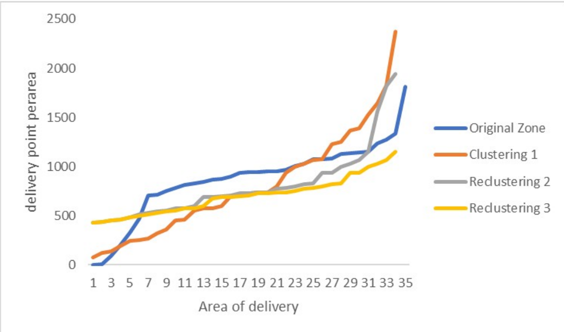

Figure 3: The number of delivery points for each area is sorted from lowest to highest.

Table 4 presents another innovative metric for assessing workload balance, which is the slope of the line graph representing the distribution of delivery points per area, sorted in ascending order. Initially, the clustering process yield a slope of 34.03, which serves as a quantitative indicator of the distribution of workloads among drivers. A steeper slope in the context would suggest a less balanced plan. After the final re-clustering step, the slope has decreased to 15.16. This enhancement signifies a 55.45% improvement in the balance of driver workloads, demonstrating the effectiveness of the re-clustering algorithm to achieving a more equitable distribution. Note that the slope decreases with each re-clustering step, which is a positive indication of the adjustment of the driver workload.

Table 4: Slope of driver's workload in each iteration.

The number of times for re-clustering	Slope
Original zone	34.03
K-Mean clustering	51.86
Re-clustering 1	31.26
Re-clustering 2	15.16

4.3 Clustering Result Using Travel Distance

For clustering based on distance between delivery points, minimizing the number of points to calculate distances is a crucial step in reducing the time required to call distance information from map API. Figure 4 illustrate the representative points for group of points that are within 0.5 km of each other. The

Figure 4: Reduce original delivery points on the map.

Table 5: Slope of driver's workload (capacity) in each iteration.

The number of times for re-clustering	Slope
Original zone	34.03
K-Mean clustering	63.58
Re-clustering 1	33.78
Re-clustering 2	27.66

representative points consolidates the other nearby points. As a result, this method reduces the total points of 30,055 to 1,352 representative points.

The results based on the distance parameter reveals that, the overall balance of driver workloads does not exhibit significant differences when compared to clustering based on geometric coordinates. Although, the shapes of the resulting delivery zones do vary. Figure 5 displays line graph comparing the number of delivery points within the area of delivery, generated by the workload balance algorithm using distance parameter. The result confirms that re-clustering method make the workload distribution more equitable.

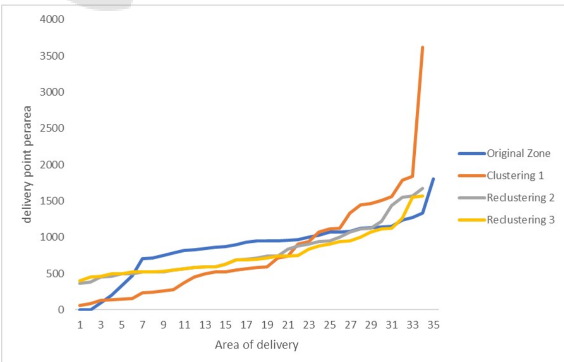

Figure 5: The number of delivery points (capacity) for each area is sorted from lowest to highest in distance.

Table 6: Slope of driver's workload (capacity) in each iteration.

The number of times for re-clustering	Slope
Original zone	34.03
K-Mean clustering	63.58
Re-clustering 1	33.78
Re-clustering 2	27.66

4.4 Zoning Analysis

Figure 6: Original Zone of Drivers.

Figure 6 showcases the original zone assignments for delivery driver, highlighting issues such as overlapping areas. These overlaps can lead to inefficiencies in delivery operations, including redundant routes, increased travel times and potential confusion over delivery responsibility.

In contrast, Figure 7 displays the outcome of the algorithm with travel distance parameter. This configuration provides new delivery areas with improvements on workload balance. However, with the visual observation, the area in the top left still encompasses two smaller zones within a larger one. These group of zones are required to have another re-clustering attempt. Additionally, the zone on the right remains quite large, potentially requires another re-clustering attempt.

For the top left zones, we can categorize these zones as under-zone and the large right zone as an over-zone. Figure 8 illustrates the outcomes of this re-clustering attempt while Table 7 lists the delivery points for the new clusters. The result zones have been improved as the right large zone is split into two smaller zones. Similarly, the top left area, which initially comprised three overlapping zones, has been redesigned into two zones. This adjustment not only reduces overlap but also ensures that the workload is more evenly spread.

Table 7: The number of delivery in clusters from re-new clustering.

The zones	the number of delivery points
Top left1	824
Top left2	1125
Big right1	949
Big right2	491

Figure 7: Partition zone obtained by the algorithm and distance parameter.

Figure 8: Final workload balance zone.

5 CONCLUSIONS AND FUTURE WORK

This study introduces a two-phase algorithm designed to strategically zone urban delivery area, with the primary goal of achieving a balanced distribution of driver workloads. The methodology combines the use of a clustering algorithm with quartiles to systematically organize delivery points into efficiently manageable zones. This study investigates the effect of the algorithm when using geographic coordinates and the travel distance to ensure that the result is practical and reflective of real-world delivery logistics.

As we show in the study, the algorithm practically improve the delivery zones by removing overlapping areas. Re-clustering procedure can also applied to make more equitable workload, comparing to a simple clustering method. Thus, this enhancement refines the cluster to ensure that the workload is less varied among drivers.

Future research from this study should concentrate on the dynamic of daily delivery operations within the predetermined zones. The challenge of effectively assigning delivery points to drivers on a daily basis, while ensuring an equitable distribution of workload, is central to optimizing last-mile delivery logistics. A key aspect of this approach involves the development of a system capable of intelligently managing delivery orders, potentially by delaying certain deliveries to subsequent days. This mechanism would aim to balance workloads more evenly across adjacent days, addressing the variability in daily delivery demands.

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