Service Points logistics and capacity cost optimization in Maastricht

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Abstract

Service point locations have been left unmodified in Maastricht for years despite the constant changes in the city infrastructure demographic and new challenges presented by a post-pandemic market. These developments resulted in a difficult year for delivering companies, who are now struggling to achieve profitability. This has led to an urgent need for restructuring, cost reduction, and improving margins, which can be achieved by redesigning the service point and delivery strategy. In this paper, we will present a solution to optimize the cost of service point location and discuss the impact of those changes. We will go in-depth about how we used XGboost for delivery demand prediction, the Dijkstra algorithm to find the shortest path from service points to residential areas and Simulated annealing to find a very feasible solution to our cost optimization problem in a relatively much lower processing time than it would take to find the best possible service point locations for Maastricht.

Keywords: *Optimization, XGboost, Facility Location , Dijkstra algorithm, Simulated annealing, cost optimization problem*

Contents

1. Introduction

The post covid-19 era shows a change in consumer behavior, with online shopping increasing in popularity [1]. This results in new challenges and opportunities for the delivery industry since last-mile delivery is proven to be an important aspect in customer decisions [2]. With hundreds of packages being delivered on a daily basis in Maastricht our task is to find strategic locations of service points to minimize delivery costs and improve customer satisfaction.

Firstly, we used *Statistics Netherlands*[1] to extract valuable data for us to use to predict delivery demands. For that used historical data from the previous annual reports, to cross-check the efficiency of our prediction models, namely XGboost and Random Forest, for which we deducted a better accuracy using XGboost.

Our next step was finding the shortest paths from one service point to the customers and using geographical data from *OpenStreetMap*[2] and implementing the Dijkstra algorithm.

Last but not least, we implemented the Simulated Annealing algorithm which allowed us to explore hundreds or thousands of possible combinations of service point locations and identify the most cost-effective layout while considering constraints like bounce rates and service point capacities.

2. Literature Review

2.1. Heuristic approach for facility location

Dealing with the facility location problem requires an approach that can deal with a complex problem in a relatively fast and successful way. According to Boujelben et al. (2016), "The heuristic method provides good quality solutions while significantly improving computation times" [5]. Heuristics such as simulated annealing have been proven to be able to overcome local optima and consistently obtain high-quality solutions. [6]. According to Murray et al. (1996), "The results demonstrated that simulated annealing is a very successful and competitive solution approach for both of these location planning models in terms of identifying optimal solutions and mean solution value. These findings along with other published studies suggest that simulated annealing is in fact a viable alternative for solving location models in general."[6] In our paper, we used the insights presented in the paper and applied similar approaches such as simulated annealing in order to find a more optimal layout.

2.2. Forecasting demand problem

Short-term forecasting represents a key factor in providing an optimal solution. The paper written by Wang [7]. dealing with this problem has identified XGBoost as an efficient method that stands out for its ability to improve forecast accuracy and avoid overfitting. For the Postl solution demand represents a key factor, making sure we accurately predict it is a key aspect in maintaining the cost low and offering customers the best experience. Similarly, the daily load demand for electricity in

[1] For further details, see [3].

[2] For further details, see [4].

the industrial context presents similar challenges and needs. There are however some differences in approaches, including the different industries, and the use of SVMD (Singular Value Decomposition and Mode Decomposition) in combination with XGBoost.

2.3. Shortest delivery route

The distance between the service point and the customers is an essential part of determining the optimal location of the service point. Dijkstra's Algorithm has been proven to be effective in this context [8]. When compared to other approaches in the context of finding the shortest path Dijkstra's Algorithm can find the optimal solution but becomes inefficient for large-scale problems [9]. However, in Soltani's paper, additional constraints such as low risk and high visibility are included which are not considered for our problem. As such we don't encounter as many drawbacks from using this approach, making Dijkstra's Algorithm an optimal approach for our problem.

2.4. Capacity planning problem

When considering capacity an appropriate value must be decided on in order to achieve the best customer satisfaction while maintaining costs as low as possible. This problem has been explored extensively with different approaches being developed to provide the optimal solution depending on different conditions, circumstances, and levels of certainty. Given uncertainty is composed of a finite set of possible outcomes with a known probability one way to approach this problem is to use a scenario-based approach to determine the capacity sizing [10]. The article also compares multiple solutions, one where short commitment horizons for lease or rental contracts are offered and one focused on long term contracts. The study concludes that the second one is more appropriate for real-world applications, which coincides with our approach. We used a similar approach in our findings to keep the bounce rate within the desired range while minimizing costs. Additionally, the paper deals with different types of customers who have different expectations, we used the insight to approach our own problem by classifying customers based on their preferences and likelihood to pick up the order.

3. Problem Definition

Our problem is under investigation as a set of decisions on logistics and capacity cost optimization by strategically selecting appropriate locations for service points in Maastricht. This problem can be split into 2 sub-problems, Delivery estimation and Service point selection. Delivery estimation consists of predicting the client's choice whether opting for package delivery or picking it up himself. Secondly, to increase customer satisfaction while minimizing delivery costs, we have to find the shortest route to get from point A to point B. After finding the best routes, we need to attend to the second sub-problem which is Service Point Selection. Service Point Selection consists of selecting service points located in strategic positions that optimize the cost of delivering packages to the locations we anticipated in the delivery estimation sub-problem.

Our training data for the delivery package sub-problem is the past years' annual reports as historical data. Some of the important data extracted were demographic data for each neighbourhood of the city, including variables such as age groups, gender, and income, alongside the number of pick-ups and deliveries for the individual service points [3]. For the Service Point Selection, we use geographic data from [4] [11] as our dataset.

Our current service points are situated in poor strategic locations. Tackling the sub-problems stated above will lead us to solve our main problem. The following methodologies will showcase our attempt to solve it.

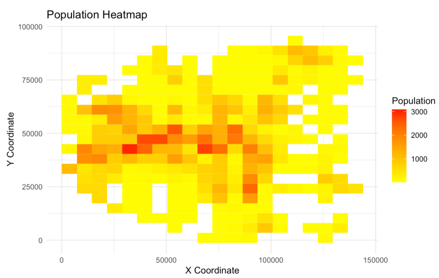
4. Initial Steps

In our initial steps, we tried to understand our dataset. The provided data had to be cleaned first and foremost. Many entries had missing values, due to low population and privacy reasons, mostly in the demographic information section. We decided to remove any information about the squares that had more than 22-24 missing values. Since these squares had a low population it should not affect the predictions. After cleaning the data we constructed initial EDAs such as the following:

4.1. Customer Analysis

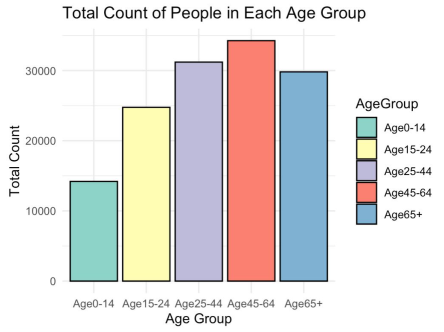
We constructed a population heatmap to see more densely populated squares. Seeing the population distribution helped us identify squares where the service point would have higher demands, which means that more packages would be delivered and picked up, hence resulting in higher costs.

The figure below shows a heatmap of the population heatmap of Maastricht.



After identifying the densely populated areas we turned our interests toward the demographic of these areas (Fig. 2). We looked at the age group of the total count of people in the city. We see that the population has the highest Age distribution of between 45-62. We can see that the graph is left skewed hence the population has a higher age on average. With this initial information, we deduced that the number of deliveries could be higher than pickups, because higher age can point towards higher financial stability, as well as with higher age people would be less likely to pick up since they don't want to make the trip due to health complications. I would like to point out that these findings are initial and cannot be taken at face value.

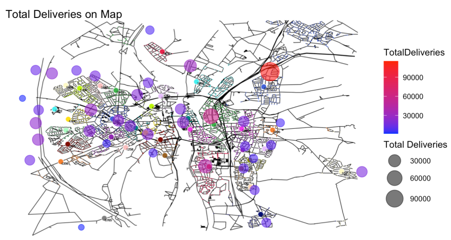
The figure below shows a bar chart of the total count of people in each age group.



4.2. Deliveries demand visualisation

After the age distribution, we looked at total deliveries over the map of Maastricht. We entered the locations of each service point and allocated the right number of deliveries to each of them. With this, we can see which service points are handling the most deliveries, which can be valuable information for closing the service point or opening an additional one for high demand. We can see from Figure 3 that most of the service points are handling between 30 and 60 thousand deliveries per year, while a couple have less hence they are more likely to be closed down. We can also see that at the top right corner, there is a service point that handles more than 80 thousand deliveries, which may be too much and might require opening an additional service point nearby. Overall our initial data exploration and EDA provided us with a better overview of the dataset we got, and from here on we can focus on building an algorithm that will help us with minimizing the costs and reworking the service point network.

The figure below shows the total deliveries of the current service points in a year.



Needless to say, findings with regard to the population of Maastricht and the client's existing customer base are not restricted solely to optimal network optimization. We believe that our insights and analysis have uncovered rather interesting information that could be utilized by other segments of the client's operations such as the marketing department.

5. Methodology

5.1. Delivery and Pickup Estimation

5.1.1. Dijkstra's Algorithm

Our company aimed to refine the assignment of geographic squares to service points, ensuring that both deliveries and pickups are conducted in the most time-effective manner possible to separate your company from its competitors. We began by employing routing algorithms such as Dijkstra's [12] to calculate the shortest paths within a directed graph framework. Dijkstra's algorithm was conceived by a Dutch computer scientist E. W. Dijkstra in 1956. This algorithm finds the shortest path between nodes in a weighted graph which, as in our case, can represent a road network. Figure 4: Output of Dijkstra's algorithm (left) represents the output of Dijsktra's algorithm. It essentially displays a rough estimate of which service points (marked by red circles) services are located. This schema can be used by the logistics department of Post&l in the route planning process to ensure efficiency and timeliness or for resource allocation by showing where more vehicles or resources might be needed based on the concentration of routes and their frequency. Finally, we've calculated probabilities for pickups and deliveries based on the average distance from the nodes within a square to the assigned service point. If the distance is less than 200 meters, the pickup probability is high (80%), and the delivery probability is low(20%). If the distance is 2000 meters or more, it assumes no pickups will occur (probability of 0 % for pickups, 100 % for deliveries). For distances in between, the probabilities are interpolated linearly.

In mathematical terms, Dijkstra's Algorithm is the following:

- $\text{dist}[v] = \infty$ for all vertices $v \neq s$, where s is the source node.
- $\text{dist}[s] = 0$.

Relaxation

For each edge (u, v) with weight $w(u, v)$:

- If $\text{dist}[u] + w(u, v) < \text{dist}[v]$, then update $\text{dist}[v] = \text{dist}[u] + w(u, v)$.

Algorithm Steps

1. Initialize a priority queue with the source node s.
2. While the queue is not empty:
    - Extract the node u with the minimum distance.
    - For each neighbor v of u, perform the relaxation step.
3. Repeat until all nodes are processed.

Shortest Path Calculation

The shortest path from the source node s to any node v is given by $\text{dist}[v]$.

5.1.2. Feature engineering

The raw data currently available is still primitive; modifying and sorting it in some ways could unveil many more features that would improve our research and tackle our problem more efficiently for supervised learning; which was touched upon by [13]. In this case's datasets, we modified and extracted variables like weighted mean age, income midpoint, and average distance to service points per square. The weighted mean age variable is simply the average distance to service points per square. The weighted mean age variable is derived by using age group midpoints, while the income midpoint adjusts income brackets to single values. Additionally, the historical datasets were transformed to analyze trends and assess not only the predictive power of each variable on our problem but also the impact of one variable on another.

5.1.3. Predicting Demand

To move forward we had to predict demand for deliveries and pickups. We explored two algorithms, the Random Forest [14] and XGBoost [15], and later on compared them to see which one produced better results.

5.1.4. Random Forest

We decided to try out the Random Forest for predicting, as it is useful to model feature interactions. We merge our historical data with the new feature-engineered data to our dataset to uncover more insight and get even better predictions. Only then, we could apply the Random Forest algorithm by Breiman Leo. The following is the result of our prediction:

RF Pickups Model Eval	RF Deliveries Model Eval
MAE: 15.859	MAE: 18.022
MSE: 642.56	MSE: 1694.33
R2: 0.788	R2: 0.702

After conducting this analysis, the most prominent features for deciding demand were the Average distance to the service point and whether it is a working day or not. These are all important features for the customer and therefore our Random Forest model puts high importance on it too. The Random Forest model had the following evaluation metrics:

MAE represents the mean average error, MSE is the mean square error and R2 is the R squared metric. The mean average error metric represents the average magnitude of errors.

The mean squared error measures discrepancies between the predicted and the actual values. After doing so we can see that the mean squared error suggests about ± 25 ($\sqrt{642.56}$) package difference from the actual values for pickups and ± 41 ($\sqrt{1694.33}$) packages for deliveries. The R-squared metric represents the goodness of fit of our model. This gives us an idea of how well-unseen cases can be predicted with our model. The higher the R squared value is the more ideal it is. We can see that it is 78% correct for pickups and 70% correct for deliveries. Overall our model provides a good overview of how the demand is in Maastricht and can predict a decently for unseen case.

5.1.5. XGBoost

Moving onto the other model we tested out: the XGBoost. This model can work with high accuracy and speed. It is ideal for predicting variables, hence, we choose to predict demand with it. We prepared the same feature importance diagram and model evaluation for this model too. The most important value of this model was the IsWorking feature. Summarizing the feature importance for XGBoost we can see that IsWorking and Average distance to service point are the most important features that XGBoost pays attention to. Moving onto the model evaluation we get the following results:

XGboost Pickups Model	XGboost Deliveries Model
MAE: 14.649	MAE: 14.31
MSE: 539.95	MSE: 1047.10
R2: 0.822	R2: 0.816

We can see that this model produces lower values for MAE and MSE, and produces higher values for the R squared. Since the accuracy of the XGBoost model is higher and the error in prediction is lower. Therefore, we will evidently use XGBoost as our predictive model for this Delivery Prediction sub-problem.

5.2. Optimizing Strategy - Simulated annealing

For our optimization strategy, we decided to use a simulated annealing algorithm as it is commonly used for similar postal service routing problems,one of which is [16]. Simulated annealing will help us find a more optimal layout. Simulated Annealing deals well with complex optimization problems while being relatively simple and easy to implement, without complex mathematical structures. It allows a large range of flexibility, being able to interplay between the discrete, continuous and combinatorial problems. In our case, it helps combine the problem of layout/location of service point optimization, with optimizing the cost function, which are, respectively, discrete and continuous problems in nature. Simulated annealing helps find the best solution by exploring many options and sometimes accepting worse ones temporarily. This approach prevents the method from getting stuck in less optimal solutions, which can happen if it only tries to improve on the current solution. By allowing some flexibility, simulated annealing has a better chance of finding a more optimal solution overall. We've implemented the Simulated Annealing algorithm in our model as follows. First, we estimate the service point capacities and costs using the pick-up/delivery possibilities we've predicted previously. One complexity we need to implement in our optimization problem is that we want to ensure that the city-wide and service point-based bounce-back rates of 1% and 2% respectively are respected.

We can compute the relevant variables as such:

For each square i assigned to a service point j:

$$\text{AvgDist}(i) = \frac{1}{n_i}\sum_{k=1}^{n_i} d_{ik}$$

where d_{ik} is the distance from square i to node k, and n_i is the number of nodes in square i.

■ Capacity Constraints

Ensure the service point j can handle the load:

$$\text{Capacity}(j) \geq 0.98 \times \text{Predicted Load}(j)$$

■ Total Cost Calculation

The total cost for a configuration of service points:

$$\text{Total Cost} = \sum_{j=1}^{M} (\text{AvgDist}(j) \times \text{Delivery Volume}(j) \times 0.5\,\text{EUR/km})$$

To manage peak days and prevent exceeding service point capacities, we implemented simulated annealing algorithm under the bounce rate constraint; to abide to this constraint, we used confidence intervals to achieve this: 98% for individual service points and 99% for the network as a whole.

Simulated Annealing works by iteratively generating "neighbour" solutions, which involves either adding or removing service points. For each combination of service points across Maastricht, the algorithm recalculates distances, capacities and costs based on these new configurations and compares them to the current solution. From time to time, the algorithm may accept worse solutions to explore a broader range of possibilities. As iterations proceed and more combinations are tested, the acceptance rate of those worse solutions decreases, guided by a temperature parameter that gradually cools down with a cooling rate. This controlled approach helps to escape a local optima - where the neighbour solution of this current solution is maxed - and tries to find a more optimal overall solution.

The simulated annealing annealing process can be mathematically quantified as:

Define a cost function C that measures the total cost of a given configuration of service points and routes:

$$C = \sum_{i=1}^{N} (D_i \times c)$$

where D_i is the distance for route i and c is the cost per kilometer.

Temperature Schedule

Initial temperature T_0. Cooling schedule: $T_{n+1} = \alpha \cdot T_n$, where $0 < \alpha < 1$.

Acceptance Probability

For a current state s with cost $C(s)$ and a new state s' with cost $C(s')$:

- If $C(s') < C(s)$, accept the new state.
- If $C(s') \geq C(s)$, accept the new state with probability:

$$P(\Delta C, T) = \exp\left(-\frac{\Delta C}{T}\right)$$

where $\Delta C = C(s') - C(s)$.

Algorithm Steps

1. Initialize with a random configuration s and initial temperature T_0.
2. While $T > T_{\min}$:
   - Generate a neighbouring configuration s'.
   - Calculate the cost difference $\Delta C = C(s') - C(s)$.
   - If $\Delta C \leq 0$, accept s' as the new state.
   - If $\Delta C > 0$, accept s' with probability $P(\Delta C, T)$.
   - Update the temperature T according to the cooling schedule.
3. Repeat until the system is sufficiently cooled.

6. Results and Analysis

As per the historical data we received, the cost of running a service point is estimated to be €75,000 this year. This is the most dominant cost we would have to incur by far compared to delivery cost which comes second and finally the storage cost. Initially, we have 35 operating service centers which alone accounts for a whopping €2.625 million. Followed by almost €500,000 for package delivery and lastly, €100,000 for storage costs. Summing up to nearly €3.2 million, this is our initial value. On the other hand, with factual analysis, we conclude that we can save a substantial amount of money by closing the majority of current service points and opening new ones in more centralized areas in order to cover the vast majority of Maastricht districts. As stated earlier, we use simulated annealing to find a very feasible solution for the minimization of our total cost in a realistic amount of computing time. The optimal solution of that particular algorithm stated a spectacular total cost of €672,000, with 7 service centers located at the following service points ID: 99, 386, 1030, 4142, 5897, 6171, 8485. Those changes will save us around €2.5 million.

The diagrams below compare the initial locations against the newly created optimal locations. As stated before, the optimal solution involves building new service point locations in such a manner that all major areas of Maastricht are covered to ensure customer satisfaction while saving more than €2.5 million in costs. Below is the table of the optimal location While it can be seen as "merely a prediction", our model's accuracy does not share the same opinion as its uncertainty is around 25 packages every day which adds up to, in the context of your business, a negligible uncertainty of 9000 packages being delivered or stored by each location. A rough overestimation of this uncertainty can cost us at most €100,000 more than predicted. Yet, amidst these calculations, we still managed to retain a net positive of €2 million. The optimal locations can be seen to have a good combination of several factors that give a nice logical idea of why they might be optimal. First of all, all of the newly created locations are around 1 km from a supermarket, suggesting why they do not opt for deliveries which is more costly for Post&l than storing the package as people usually go to the supermarket and fetch their parcels on the way. The service location points are a mix of urbanization index areas, which means that they get to cover all deliveries to both quiet places as well as places with a lot of hustle and bustle.

7. Assumption(s)

In the whole attempt to solve this optimization problem, we made an assumption about the distance from a service point to a node in a 500m*500m square. We calculated the average distance it takes for a service point to reach a node in the square. Then for every other time we make a delivery, we calculate from the average distance calculated rather than the actual distance. Nevertheless, the difference will not be huge as the squares are 500m * 500m. In the worst case, we can have an error of 250m which is a loss or profit of 0.25 * 0.5 (fuel cost per km), which is 12.5 cents per trip. In Maastricht, there were approximately 80,000 deliveries made in recent years, which in the worst case can result in a miscalculation of €10,000 which is negligible. The trade-off was far more rewarding as using this assumption, we did not have to calculate the exact distance every time which saved us a whole lot of processing time, thus, a lot of service point combinations could be selected in our simulated annealing algorithm. [17]. backs up the idea of using somewhat inaccurate approximations to allow the algorithm to explore deeper as a trade-off.

8. Limitations

After reviewing multiple papers addressing similar problems we were able to identify some aspects that are not properly addressed in our solution. This aspect could affect the feasibility of our solution application.

8.1. Last Mile Delivery Logistics

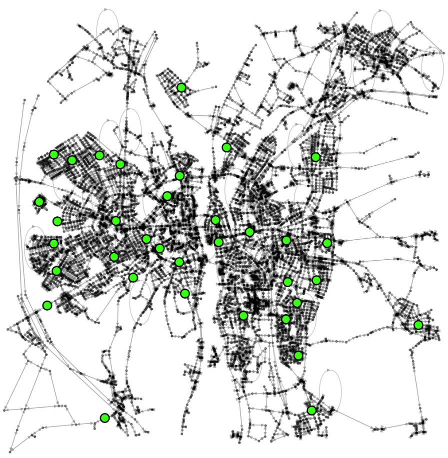
When deciding on the optimal solution we do not take into consideration some logistics challenges that can appear in a real-world scenario. Some of these challenges include the availability of parking spots and failed first-time deliveries [18] or an aging population which could affect the ability to hire the required workforce [19]. To solve this challenge multiple approaches are presented and considered [20]. In this paper, Boysen et al, (2021) present some possible alternatives to improve the last-mile delivery process. In the paper, the solutions are presented based on the timeline of viability, specifically present, near future, and far future. For today's concepts other than the methods that we have already considered he presents alternatives such as self-service or cargo bikes which present the advantage of being able to reach customers residing in areas with access restrictions such as pedestrian zones or places with limited parking space. [21]. In the near future Boysen et al, (2021) consider Drones, autonomous delivery robots, alternative handover options, or crowd-shipping. He explores how these options can solve some of the challenges presented, such as integrating crowd shipping into the delivery enabling a flexible option that can relieve some of the challenges posed by an aging population.In the farther future delivery concepts such as alternative drone launching platforms, autonomous driving, and tunnel-based cargo transport are elaborated. For our problem approaches proposed in the current and near-future can provide insight and possible solutions that can improve our model, minimize cost, and make the application more feasible and realistic.

8.2. Sustainablity

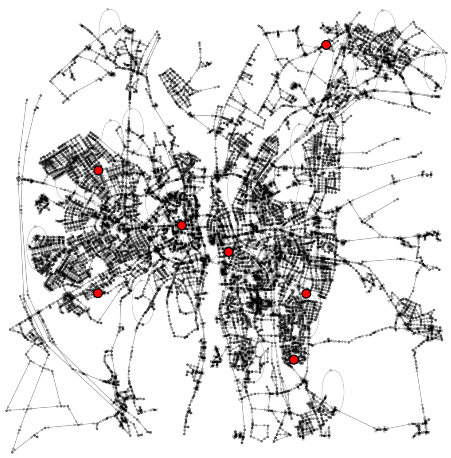
While deciding on the optimal solution one key aspect that has been neglected is the sustainability aspect. As this problem becomes more recognized many companies will need to adjust to meet the sustainability criteria and to include the cost of externalities which are not properly considered or valued in the current approach. Challenges for sustainability in our case are a result of increased transport-related problems such as gas emissions, traffic delay, accidents, air and noise pollution, and damage to infrastructure [22]. This problem has been explored by [23], with multiple approaches for improving sustainability being offered, including the usage of light vehicles which are more sustainable alternatives to large trucks and choosing a more environmentally friendly energy alternative for vehicles. Another key aspect presented for improving sustainability is the distribution center location, with innovation such as a mobile distribution center being considered in certain places where building a facility is less desirable or not feasible [23]. Another important aspect being explored is the improved sustainability aspect of pickups compared to home delivery with carbon emission being significantly higher in the latter case [24]. Using these findings as insight we can find a solution that takes into account the sustainability aspect.

9. Conclusion

In conclusion, we strongly suggest having a significant decrease in the number of operating service centers due to the simple fact that operating expenses for running a single service point have a huge annual cost of €75,000. The service centers should be located in easily accessible locations with uncomplicated access to the city center whilst remaining a reasonable distance from less urban areas. As stated before, a very feasible solution involves opening 7 service centers located at the following service points ID: 99, 386, 1030, 4142, 5897, 6171, 8485 saving us more than €2.5 million. As well as saving costs, the downsizing from 35 to 7 service points will only prove beneficial to the operations of Post&l, by reducing the need for staff, ultimately minimizing operating costs.



(a) Initial Service Points



(b) Final Service Points

Information

This journal is heavily based on Optimization of Service Point Locations Report[a]

[a]For further details, see [25].

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