

Modeling the vehicle routing problem considering bicycles

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ABSTRACT

The vehicle routing problem is a well-known combinatorial optimization problem with many variations and real-life applications. One variation analyzed here has to do with the type of the vehicle being used, in this case bicycles. Many logistics companies have started using bicycles to carry out deliveries in city centers. There are advantages such as bicycles can better cope with congested routes and ensure faster and reliable deliveries, they don't pollute the environment, and they cost less. In this article we review how to make a simple adaptation on the popular CVRP (capacitated vehicle routing problem) and the VRPTW (vehicle routing problem with time windows) to accommodate the extra effort when climbing hills.

KEYWORDS. Bicycles. Vehicle routing problem. Mathematical modeling.

Paper topics: OC – Combinatorial optimization. PM – Mathematical Programming.

1. Introduction: Can bicycles support logistics services?

Have you ever been in a situation where you were inside a nice car, capable of moving from zero to 100 km/h in just few seconds, but completely stopped because of a traffic jam? Then, you see the traffic lights changing from red to green, then from green to yellow, to red again and you didn't move even one meter! Then, a bicycle passes you and you start wondering how good it would have been if you were riding a bike instead of your nice car! You start saying to yourself that if you were riding a bike, you would already be relaxing at home. If you live or work in a city center, probably you already saw yourself in such a situation. Needless to say, bicycles are gaining more importance and popularity nowadays.

Bicycles are being used not only for people's locomotion but also for delivery of goods. In this last case, we can see bikes from bakery stores, clothing washing stores, pet shops, and so on, making their deliveries. Same with food delivery services which gained even more popularity during the covid-19 pandemic crisis. More than that, with the growth in the online purchasing business, we can see some logistics companies using bikes to perform the last mile delivery instead of traditional vans or trucks. This is where bikes can bring advantages to logistics services and where there is a change of mindset breaking some paradigms.

Can bikes offer a better delivery service than vans? Depending on the situation the answer is positive. A good portion of the number of deliveries in cities are not related to big volumes moving from point A to point B. Rather, it involves transporting many low volume items to be delivered to several points scattered in a particular neighborhood (a classic vehicle routing problem). Furthermore, we have the considerations of the environment of many big cities: congested streets, traffic jams, rush hours, restrictions forbidding the circulation of vans and trucks during certain time intervals, lack of parking areas available and high cost associated with that. Reality is that serving the last mile inside cities is a complex topic for logistics services. If we visualize a van that needs to deliver 3 small items in 3 different locations apart 3km from each other in a rush hour and we compare that with a bike capable of carrying these 3 items together and circulating among cars stuck in congested streets and even making use of sidewalks when needed, then we can easily see which one will complete the service faster. Therefore, more reliable delivery promises and customer satisfaction may be achieved by using bikes to support the last mile delivery in an environment like the one described here.

Besides the possibility of being faster in a congested city center, bikes address another major logistics concern. Bikes cost less. The acquisition price is much lower, maintenance and insurance costs are lower, and there is no fuel consumption which is also an important cost factor. Talking about no fuel consumption, we have already experienced situations where the fuel price increased considerably bringing a strong pressure over the supply chain overall cost. Bikes can reduce this impact. Moreover, there is even another point that is catching a lot of attention recently. Bikes are a green solution for delivery services. They don't increase the pollution in cities which is aggravated by vans, cars and trucks driving very inefficiently in congested streets. Thus, bikes help in reducing CO₂ emissions. The earth thanks for that!

The idea seems interesting but how realistic is to expect that bikes can replace vans? How much of the goods currently transported by vans could be handled by bikes?

Fortunately, there is a good amount of research aiming to answer these questions. For instance, according to CycleLogistics, an EU Project, around 25% of all goods and 50% of all light goods can be switched from traditional delivery vehicles to bicycles in urban areas [Ferguson 2012]. Reality is that in some cities, the potential may be even higher. Another study indicated that the average weight carried by motorized vehicles in European cities is less than 100kg while bicycles can carry weights even heavier than 200 kgs depending on the bicycle type [De Decker 2012]. This last sentence breaks a view that bikes are suited only for small volumes or small weight. Special bikes have been designed to carry a good amount of weight. Therefore, depending on the type of bikes used, the potential of moving cargo from vans to bikes can be considerably high. The

same study pointed out that bikes can cost 98% less than vans. Here, it is not only the acquisition price but considers all associated costs for both type of vehicles. Furthermore, the concern that more people will be required because more bicycles are required to do the job of a van is not a truth written in stone. When dealing with delivering goods inside the city, bicycles may in some cases be faster and therefore deliver as much goods as a van does. An interesting study looked at the travel time difference between bicycles and cars, concluding that for the type of environment present in many urban cities, around half of the deliveries can be switched from cars to bicycles with a delay of no more than 10 minutes [Gruber and Narayanan 2019]. Thus, more drivers are not mandatory and the argument that we would switch from less costs for running vans to more labor costs for paying more people riding bikes disappears. All these factors are relevant considering that last mile logistics is viewed as the least efficient stage of supply chains and can make up 28% of the total delivery cost [Ranieri et al. 2018]. Considering that a little over half of the population live in cities and the trend is that it increases in the next few years, then looking at last mile efficiencies opportunities is something that cannot be ignored [Naumov and Pawlus 2021]. Moreover, the transportation sector is responsible for approximately 23% of global CO₂ emissions. So, switching cars to bicycles also brings the attractiveness of bicycles being a “green” transportation vehicle [Massink 2011]. A good literature review of usage of bicycles to deliver goods in cities and different approaches is listed in the bibliography [Vasiutina et al. 2021].

Another interesting study compared some scenarios and demonstrated that cargo bikes are more cost effective than delivery trucks when considering deliveries happening in an area near the distribution center while delivery trucks are more cost effective for higher distances and large volume deliveries to one stop [Sheth et al. 2019]. Companies offering bike delivery services have announced that bikes can make up to 30 deliveries and travel for 80km during a day. Of course, depending on sizes and weights number may vary.

We have addressed some points such as costs, speed and reliability for last mile deliveries inside congested cities, less CO₂ emissions, and other associated benefits. However, we can also mention the health benefits for the bikers. The physical exercise generated by riding a bike can help in preventing strokes, heart attack, obesity, depression and other diseases.

Considering all this research that was published and quoted above, we can confirm that depending on the situation, bicycles can be a feasible and attractive solution for the last mile deliveries. It can be the case when dealing with deliveries scattered in congested city centers and also when carrying low volume and low weight packages. They can be cost-effective and also contribute to a reduction on CO₂ emissions.

Based on all the above, we can consider the problem of having goods stored in a distribution center located inside the city and from there several bikes will depart, each one carrying a number of items to be delivered to several customers scattered throughout the city. This is the typical vehicle routing problem as we know in the field of operations research and combinatorial optimization. Would there be any modification to account for bikes as the vehicle type? It may depend on the city geographical topology. Basically, bikes may have to overcome hills when serving a particular route. The physical effort to go from point A to point B passing through other intermediary points may be considerably less than going from A directly to B if B is in a hill. This article offers a simple methodology to consider hills when selecting the best routes in the vehicle routing problem.

Here we will analyze two versions of the vehicle routing problem. The first is the classical capacitated vehicle routing problem (CVRP) where a load capacity constraint is taken into consideration. The second adds time windows (TWVRP) where the vehicles need to arrive and leave a customer always inside a time window which is particular for that customer. In both cases the vehicles depart from a distribution center and end their routes by returning to distribution center. Each customer is visited by only one vehicle and only once. Optimizing these problems takes us to

a minimum number of vehicles (bicycles) as well as specific routes for each vehicle in such a way that the minimum cost (or minimum travel distance) is achieved.

Both the CVRP and the TWVRP are well known problems. The capacitated vehicle routing problem was introduced by [Dantizg and Ramser 1959]. Since then, considerable research has been done on this combinatorial optimization problem and an extensive literature is available considering not only the variations on the problem formulation but also on methodologies for solving it [El-Sherbeny 2010], [Goel and Maini 2017], [Goldbarg et al. 2016], [Kumar and Panneerselvam 2015], [Laporte 2007], [Laporte et al. 2013], [Liong et al. 2008]. In this article we explore these problems by adding a small variation to account for the effort from a bicycle to face hills when moving from one customer to another. It may be possible that the climb from a customer to another may be too steep to be performed by a bicycle. Basically, we penalize the objective function when the inclination angle from one customer to another is higher than a specified threshold. By doing so, the problem looks for routes that smoothen the climbs.

Let $G = (V, A)$ be a graph with $V = \{0, 1, 2, \dots, n\}$ as the vertex set where 0 is the distribution center from where all vehicles will depart and finally return. All other nodes represent the customers, and each customer has a demand q_i associated with it. Besides the vertex set, we also have the arc set $A = \{(i, j): i, j \in V, i \neq j\}$. This arc set contains all possible paths between one node and another, by node we mean each customer and the distribution center. Each vehicle has a maximum capacity Q and an important assumption is that $q_i < Q, \forall i \in V/\{0\}$, which means that the demand from each customer cannot exceed the vehicle capacity. The VRP is a NP-hard problem and reminds us the classical traveling salesman problem, known as the TSP. The TSP can be seen as a VRP with only one vehicle and with infinite capacity.

2. Mathematical modeling for the capacitated vehicle routing problem - CVRP

The CVRP can be modeled as:

$$\text{Minimize } z = \sum_{i,j} (c_{ij}x_{ij}) \quad \text{for } i,j \in \text{nodes}, i \neq j \quad (1)$$

Subject to:

$$\sum_{j \in \text{nodes}} x_{ij} = 1 \quad \text{for } \forall i \in \text{customers}, i \neq j \quad (2)$$

$$\sum_{i \in \text{nodes}} x_{ij} = 1 \quad \text{for } \forall j \in \text{customers}, i \neq j \quad (3)$$

$$\left. \begin{array}{l} u_j \geq u_i + q_j - (1 - x_{ij})M \\ u_j \leq u_i + q_j + (1 - x_{ij})M \end{array} \right\} \quad \text{for } \forall i, j \in \text{customers}, i \neq j \quad (4)$$

$$q_i \leq u_i \quad \text{for } i \in \text{customers} \quad (5)$$

$$0 \leq u_i \leq Q \quad \text{for } \forall i \in \text{nodes} \quad (6)$$

$$x_{ij} \in \{0,1\} \quad (7)$$

The problem above makes a differentiation of two sets, the first one is the set of customers $(1, \dots, n)$ and the second is the set of nodes that includes all customers plus the distribution center

which is both the start and end points of all routes. Assuming zero as the index for the distribution center, then we make the set of nodes $(0,1,2,\dots,n)$.

The Objective Function (1) aims to minimize the total cost of the routes. The constant c_{ij} means the travel cost from customer i to customer j . This cost may be proportional to the distance between these two points or maybe even the same, and in this case the problem becomes a minimization problem of the total distance of all routes. The variable x_{ij} is binary and equal to 1 in case the path between customers i and j belongs to any of the routes and 0 if not.

Equation (2) ensures that from each customer there will be only one route departing and going to another customer or to the distribution center ending the route. By other hand, Equation (3) ensures that in each customer there will be only one route arriving to it and coming either from another customer or from the distribution center. These two equations together ensure that all customers are visited and that it occurs only once. Therefore, a customer will not be able to belong to more than one route. However, the way these equations were built allow the departure and arrival of multiple routes to the distribution center.

Inequalities (4), (5) and (6) work together using an auxiliary variable named u that is used to calculate the capacity used by each vehicle as it moves from customer to customer across its route. The demand from customer i is given by the constant q_i and the capacity of each vehicle is given by the constant Q , assuming all vehicles are identical, meaning same capacity. In Inequality (4) M is a constant with a big value that satisfies the inequality when x_{ij} is equal to 0. When x_{ij} is equal to 1, the effect of M in the inequality is null as it is multiplied by 0. This inequality also eliminates sub-tours as a sub-tour with customers only, without passing through the distribution center, violates its construction. Inequality (6) ensures that the vehicle capacity will not be exceeded.

Expression (7) defines this problem as integer by means of the binary variable x_{ij} which can only be either 0 or 1.

3. Mathematical modeling of the vehicle routing problem with time windows - TWVRP

The formulation with time windows is a little more complex and can be expressed with the below equations:

$$\text{Minimize } z = \sum_{i,j,k} (c_{ij}x_{ijk}) \quad \text{for } i,j,k \in \text{routes}, i \neq j \quad (1)$$

Subject to:

$$\sum_{j \in \text{customers}} x_{ijk} = 1 \quad \text{for } \forall i \in \text{customers}, i \neq j, \text{ and for } \forall k \in 1, \dots, K \quad (2)$$

$$\sum_{i \in \text{customers}} x_{ijk} = 1 \quad \text{for } \forall j \in \text{customers}, i \neq j, \text{ and for } \forall k \in 1, \dots, K \quad (3)$$

$$\sum_{j \in \text{customers}} x_{0jk} = 1 \quad \text{for } \forall k \in 1, \dots, K \quad (4)$$

$$\sum_{i \in \text{customers}} x_{i0k} = 1 \quad \text{for } \forall k \in 1, \dots, K \quad (5)$$

$$\sum_{i \in \text{nodes}, i \neq h} x_{ihk} - \sum_{j \in \text{nodes}, j \neq h} x_{hjk} = 0 \quad \text{for } \forall k \in 1, \dots, K \text{ and for } \forall h \in \text{customers} \quad (6)$$

$$\sum_{i \in \text{customers}} q_i \sum_{j \in \text{nodes}, i \neq j} x_{ijk} \leq Q \quad \text{for } \forall k \in 1, \dots, K \quad (7)$$

$$b_{ik} + s_i + t_{ij} - M(1 - x_{ijk}) \leq b_{jk} \quad \left\{ \begin{array}{l} \text{for } \forall i \in \text{nodes}, \\ \text{for } \forall j \in \text{customers}, \\ \text{for } \forall k \in 1, \dots, K \end{array} \right. \quad (8)$$

$$s_0 = 0, \quad b_{0k} = 0 \quad i \neq j \quad (9)$$

$$e_i \leq b_{ik} \leq l_i \quad \text{for } i \in \text{customers}, \text{ for } \forall k \in 1, \dots, K \quad (10)$$

$$x_{ij} \in \{0,1\} \quad (11)$$

The Objective Function (1) uses the variable x_{ijk} which assumes the value of 1 if the path between customers i and j is covered by vehicle k , and 0 if not. Now we have an index k for a set of vehicles $(1, \dots, K)$ where K is the number of vehicles needed to solve the problem.

Equation (2) ensures that from a customer i there will be only one route leaving and that it will be through only one vehicle. By other hand, Equation (3) ensures that in a customer j there will be only one route arriving and it will be through only one vehicle.

Equation (4) ensures that all vehicles depart from the origin which is established as point 0 while Equation (5) ensures that all vehicles will return to the origin as their final destination.

Equation (6) ensures that the flow entering a point is the same flow leaving that point.

Inequality (7) ensures that the sum of all demands q_i from all customers i served by a vehicle k will not exceed the vehicle capacity Q .

For the remaining inequalities we have new parameters which are defined below:

b_{ik} – Variable to store the moment when customer i begins to be served by vehicle k .

s_i – Constant given to indicate how much time it takes to serve customer i , being specific for each customer.

t_{ij} – Constant given (or calculated from c_{ij}) to indicate how much time it takes to travel from customer i to customer j .

M – Value big enough to satisfy the inequality.

e_i – Constant given to indicate the beginning of the time window in which customer i may be served (specific for each customer).

l_i – Constant given to indicate when the time window to serve customer i finishes (specific for each customer).

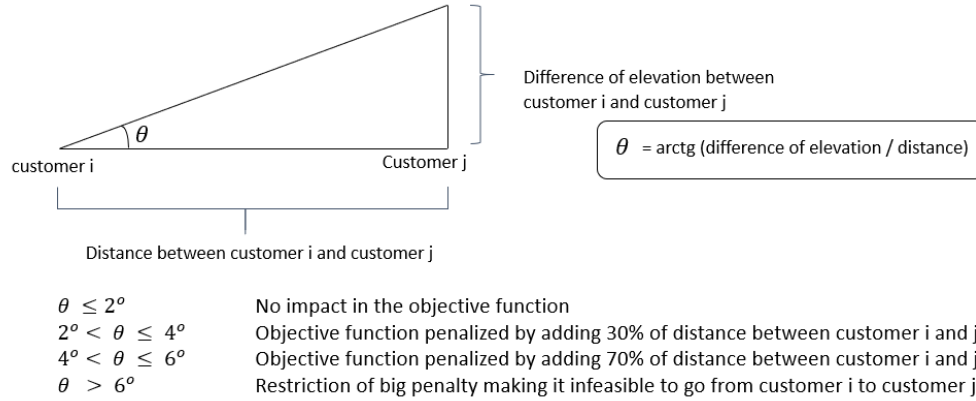
The definitions above allow Inequalities (8), (9) and (10) to ensure that all routes as well as the number of vehicles will be calculated respecting the time window constraints and eliminating sub-tours.

Condition (11) makes this an integer programming problem using a binary variable x_{ijk} .

4. Adaptation of the mathematical models to include the penalty for climbing steep hills

Since we are considering bicycles as the type of vehicles, we need to consider the impact that climbing hills can have on the choice of customers to select a route. Depending on the slope of the path from customer i to customer j , it may not be a feasible path. Therefore, the adaptation

below suggests a penalization that depends on the angle of the slope between two different customers.



If we have the difference of elevation between two customers as well as the distance between them, we can easily calculate the angle of the slope. Once we have this angle, we can see where it fits in the ranges of penalization above. The limits defining these ranges and the respective percentages for penalization were defined arbitrarily based on verification of the effort from the author in riding a bicycle in locations with these angles. Of course, these values can change from biker to biker and can be calibrated to a better approximation. Additional ranges with their respective penalizations can also be added. It is not part of the scope of this article to make an exhaustive analysis of this effort to offer angles and penalizations to reflect a more accurate view of an average biker.

Taking the problem with time window restrictions, the mathematical model can be adapted for bicycles with penalizations for climbing hills by changing only two expressions.

The Objective Function (1), is now:

$$\text{Minimize } z = \sum_{i,j,k} (c_{ij}x_{ijk}) + \sum_{i,j,k} (p_{ij}x_{ijk})$$

Here p_{ij} represents a matrix built with penalizations of distance additions depending on the slope angle. If we are considering the CVRP instead of the TWVRP, then this is the only adaptation in the mathematical model to be made. Remembering that in the CVRP we employ x_{ij} instead of x_{ijk} .

Additionally, Inequality (8) in the problem with time windows becomes:

$$b_{ik} + s_i + t_{ij} + \alpha \cdot p_{ij} - M(1 - x_{ijk}) \leq b_{jk}$$

Basically, we are adding a factor $\alpha \cdot p_{ij}$ to the time interval t_{ij} between customers i and j in order to increase this travel time in case the slope angle between them implies in a penalization. The α parameter is used to transform this penalty into an increase in time so that it can be added to the constant t_{ij} . Basically it accounts for a longer travel time between points i and j as a bicycle will experience a lower average speed when climbing hills.

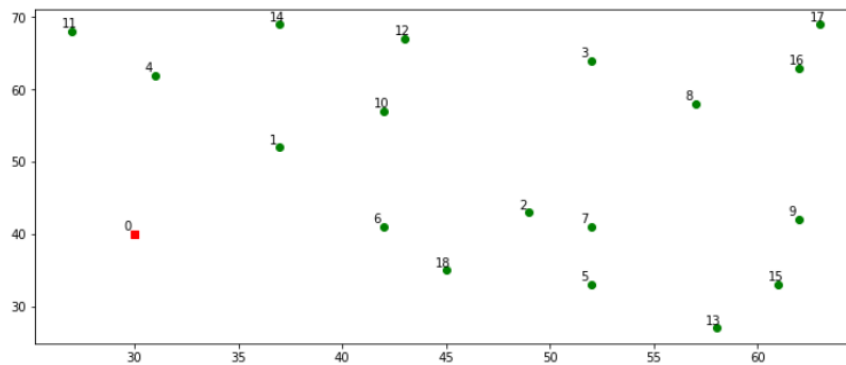
5. Computational results

The mathematical models were implemented in Python and ran in a PC using the Core i7 processor, 1.3GHz clock, 8GB of RAM memory and 256GB SSD. Two Python frameworks were used to solve the problem: PuLP and Pyomo. In the case of Pyomo, both CPLEX and Gurobi were

used as solvers. Both PuLP and Pyomo demonstrated to be excellent tools for solving these problems. Naturally, the execution time increases considerably as the number of customers increase. Because of that, a heuristic (or meta-heuristic) based solution aiming to find a “good” solution instead of the “optimal” solution becomes a more suitable approach for big size problems.

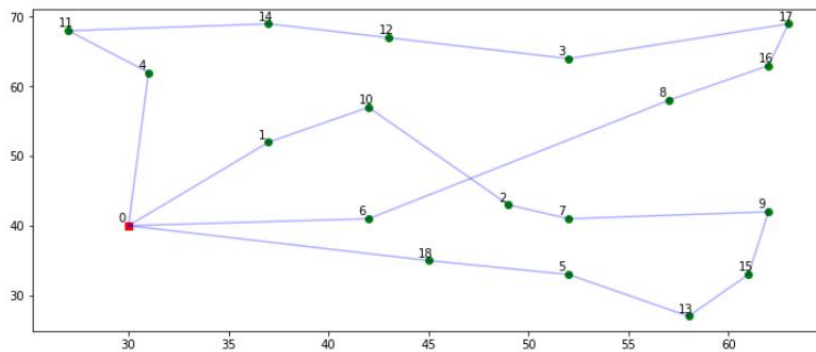
For running tests, the location data for customers was generated randomly and distances were calculated from these positions. Same thing for elevation data for each customer, also generated randomly and allowing the calculation of angles for going up or down from one customer to another.

Here we show the results obtained by using the P-n19-k2 instance of the capacitated vehicle routing problem. This instance for the CVRP contains 18 customers plus the distribution center, which is point 0, as seen in the graph below. The customer coordinates and their respective demands are shown in the table that follows. The maximum capacity for the vehicles is 160. This instance has an optimal solution of 212 using only 2 vehicles. The figure below shows the distribution of the 18 customers plus the distribution center (point 0). The distances among the points of this problem were calculated through the Euclidian method.



Point	Coordinates (x,y)	Demand
Origin 0	30, 40	0
Customer 1	37, 52	19
Customer 2	49, 43	30
Customer 3	52, 64	16
Customer 4	31, 62	23
Customer 5	52, 33	11
Customer 6	42, 41	31
Customer 7	52, 41	15
Customer 8	57, 58	28
Customer 9	62, 42	14
Customer 10	42, 57	8
Customer 11	27, 68	7
Customer 12	43, 67	14
Customer 13	58, 27	19
Customer 14	37, 69	11
Customer 15	61, 33	26
Customer 16	62, 63	17
Customer 17	63, 69	6
Customer 18	45, 35	15

We used the mathematical model for the capacitated vehicle routing problem (CVRP) implemented in Python through Pyomo, using Gurobi as the solver and we confirmed the optimal solution of 212 with 2 vehicles as seen in the figure below.

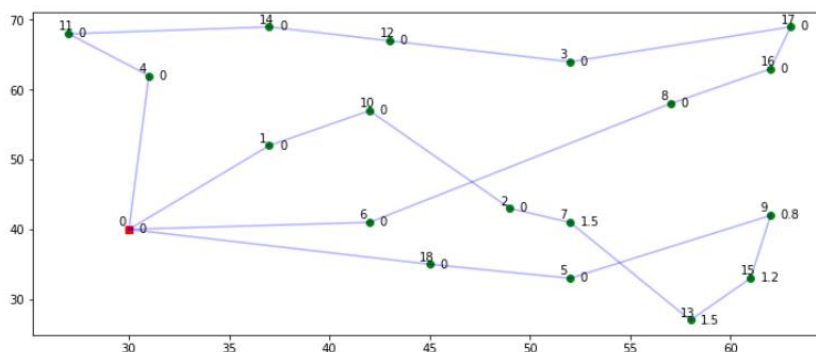


We can see two routes:

First route: 0 – 4 – 11 – 14 – 12 – 3 – 17 – 16 – 8 – 6 – 0

Second route: 0 – 18 – 5 – 13 – 15 – 9 – 7 – 2 – 10 – 1 – 0

Now, based on the above solution we can add the adaptation proposed in this article for bicycles facing differences in elevation. Let's suppose we assign elevation 0 for the origin and all other customers but customers 7, 9, 15 and 13. We assign elevation 1.5 to customers 7 and 13, elevation 0.8 to customer 9 and elevation 1.2 to customer 15. By doing so, we create an obstacle for the biker from the second route to move from customer 5 directly to customer 13 (this is the path in the second route from the optimal solution) and this obstacle is reflected in the objective function through the addition of a strong penalty. By other hand, the biker can reach customer 13 through another route passing by other smoother climbs and from them get to customer 13. We can see the new optimal solution in the next figure.



In this new configuration, there is an angle of more than 10 degrees between customers 5 and 13 which strongly penalizes the objective function. In face of this situation, the route prefers to move from customer 5 to customer 9 instead, as the slope angle is much lower. From there to customer 15, and from customer 15 to 13, and so on until the final destination. This way we can easily see that the problem looked for an optimal solution that smoothed the climbs that the biker

needs to cover. In the figure above, the numbers on the left refer to the customer numbers and the numbers on the right refer to the elevation values.

6. Final considerations

The vehicle routing problem with the restriction of vehicle capacity and the restriction of time windows are already well known. This article considered the utilization of PuLP and Pyomo from the Python language to solve these problems and proposed a simple adaptation to consider how penalties can be incorporated into the problem to account for the physical effort from the biker to cope with steep climbs. By incorporating this adaptation, the solution looks for not only the solution of minimal cost (or distance) but also a solution that smoothens the climb. The value of the penalty to be inserted into the problem will determine how much the solution will tend to look for the minimum cost of all routes or for routes that have smoother climbs.

It is important to say that depending on the topography of the city where the service is performed, the difficulty of going up hills can be totally ignored. Also, using electric bicycles can be a nice and still cost-effective way to address the problem of the last mile delivery in big cities. Anyway, using bicycles for delivering goods is an intelligent solution for big cities. It can reduce costs, can ensure a faster and more reliable service, and is also a “green” solution. As said earlier, the earth thanks for it.

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