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Improving Performance of Vehicle Routing Algorithms using GPS Data

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***Abstract* — Two important problems distribution companies face on a daily basis are the routing and tracking of a vehicle fleet. The former is being overcome by solving the famous vehicle routing problem (VRP), a generalization of the traveling salesman problem (TSP), and the later analyses GPS data to get information of the moving vehicles. In this paper a system which uses GPS data to track the vehicles, analyze their routes and improve input data needed for the algorithm for the vehicle routing problem is described. In a real-world scenario, implementing an VRP algorithm is not enough. Algorithms which analyze GPS data ensure that the VRP algorithm takes correct input data and that the driven routes are those that the algorithm proposed.**

***Keywords* — Vehicle routing problem, Identifying stops from GPS data, Estimating service time of customers**

I. INTRODUCTION

THE vehicle routing problem (VRP) is a well-known combinatorial optimization problem which appears in distribution systems, where a set of vehicles needs to deliver some goods from a depot to customers. Each customer c has some demand q_c, and each vehicle v has some capacity Q_v. Vehicles also have cost per unit of travelled distance c_v, and the distances between the customers as well as between the depot and the customers must be defined. The cost of the route is its distance multiplied by its vehicle's cost c_v. The goal is to find a set of routes, each of which has a different vehicle assigned to it, such that each customer belongs to exactly one route while the overall cost is minimized.

In practice, it is not rare for some of the customers to have a time interval during which they are available to be served. The vehicle routing problem with time windows (VRPTW) is VRP which takes time into consideration. Each customer has time window $[a_c, b_c]$ at which the vehicle must start to serve it and a service time s_c, which is the time needed to serve it. Also, the time distances between customers and between the depot and customers must be defined.

VRP and VRPTW are NP-hard problems [1], but for a reasonably small number of customers (<200), there exist some heuristics which are close to the optimal solution [2]. More importantly, when used, heuristics are better than manual routing and generally decrease company costs by 5-10%.

In practice, a big problem for implementing the algorithm driven distribution system is inaccurate input data. Distances and travel times between customers are calculated from GPS locations using popular services (Google's Matrix Distance API, Graphhopper's Matrix API etc.). Some GPS locations of customers may be inaccurate. Also, in some countries, maps are not precise enough and services may give incorrect distances and travel times. One of the problems for implementing the VRPTW algorithm in the distribution system is that the service times of the customers cannot be known in advance, so they must be approximated.

Every large distribution company uses GPS devices to track their vehicles. GPS trajectory data is data which is emitted by a GPS device and it consists of series of records. Each record contains location, time and velocity. There are algorithms that use GPS data to retrieve stops and to classify stops into working and non-working.

In this paper GPS data is used not just to retrieve stops, but to also reconstruct the order of the customers which the vehicle visited, compare that order with the planned route and, most importantly, to improve input data for the VRPTW algorithm. Methods presented in this paper are implemented in one of the largest distribution companies in Bosnia and Herzegovina.

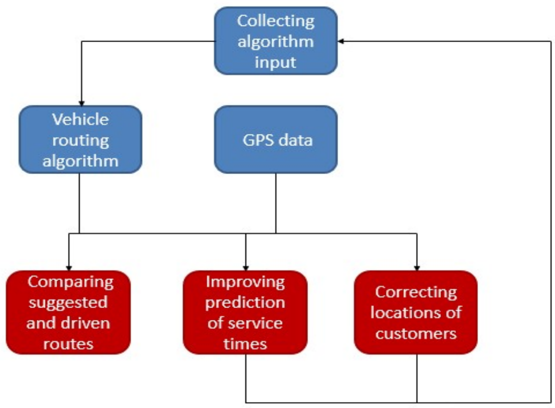

Fig. 1. Improving the VRP algorithm

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The whole scheme of improving the input data for the VRP algorithm is illustrated in Fig. 1. First of all, the input data for the VRP algorithm is collected. After that, the algorithm is executed end its results and the GPS data are used in the proposed methods to improve performance of the VRP algorithm. So, the red parts in the scheme represent the topic of this paper. Once the service times and locations of the customers are corrected, they will begin to affect future executions of the algorithm.

This paper is organized into 5 sections. In this section VRP is introduced and the importance of tracking, as well as vehicle movements analysis is presented. A literature review on related work is presented in the next section. In the third section, methods for improving input data are described. In section 4 predictions generated with the new methods are compared with previous values. In the final section some ideas for future work and a conclusion are given.

II. Related Work

Since GPS data became widely available in the 1990s, it has been the subject of many studies across many different domains.

Map matching algorithms take as their input a map and a sequence of GPS records (x, y, t) (x-latitude, y-longitude, t-time) from some time interval and to each GPS record assign a place on the map. Since GPS data sometimes gives incorrect locations, the map matching algorithms improve that location by using a map. They are used to accurately locate the vehicles, which is essential for various applications in the field of intelligent transportation systems (ITS) [3]. An overview of state-of-the-art map matching algorithms can be found in [4].

There are many algorithms which use GPS data to extract some useful information. Woodard et al. used mobile phones' GPS data to predict travel times between two points [5]. More methods which analyze GPS data can be found in a survey written by Shen and Stopher [6].

An important task in analyzing a movement of vehicles is the identification of stops. That task itself is not difficult, so research focus has gone further. Hwang, Evans and Hanke proposed an algorithm for detecting stops using GPS data with gaps [7]. After identifying stops, they can be classified into two or more classes, most commonly into working and non-working stops. Working stops are servings of customers, other stops are non-working. Gong et al. in [8] propose an algorithm which uses density based spatial clustering to identify stops, and then by using the support vector machine method classifies the stops into working and non-working ones. It can be useful sometimes to introduce more types of stops. Aziz et al. proposed a method which considers stops on a highway from a large number of trucks and congregates them into a number of clusters based on stop functionality [9].

The vehicle routing problem is one of the most studied problems in combinatorial optimization. Dantzig et al introduced it in 1959 [10]. Solomon introduced a set of benchmark instances in 1987 [11], with 25, 50 and 100 customers. For some of those instances the optimal solution is yet to be found. The focus of research in the past years moved to the metaheuristic approach. Some of the most successful are given in [12] and [13]. State-of-the-art methods which solve VRP and VRPTW can be found in the book of Toth and Vigo [2].

III. Case Study

The input for the used methods is the GPS trajectory data of one vehicle and the sequence of customers in order in which the vehicle should visit them. A part of the input is shown in Fig. 2. GPS records are green points and the blue markers are customers.

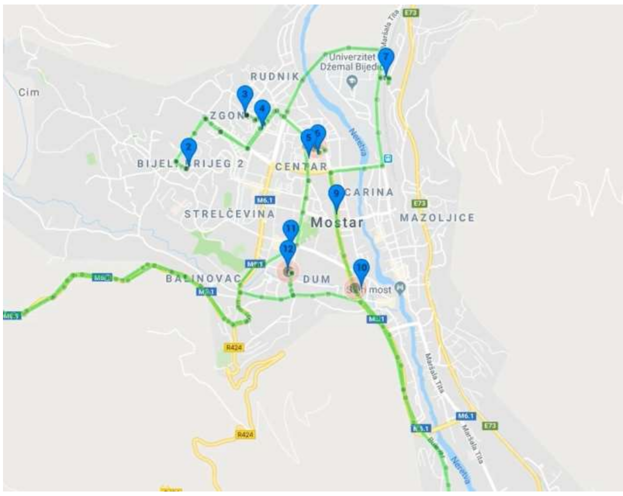

Fig. 2. GPS data and locations of customers

The analyzed GPS data P_i is given as a sequence of 4-tuples (x_i, y_i, v_i, t_i) where (x_i, y_i) and v_i represent the location of vehicles (latitude and longitude) and velocity at time t_i. It is assumed that P_i is sorted in increasing order of t_i, and that the difference between two consecutive timestamps is at most 10 seconds.

The first step of the algorithm is to retrieve a set of stops S which are potential servings of customers. The array P_i is divided into groups of consecutive timestamps where the velocity is equal to 0, and groups of consecutive timestamps where the velocity is greater than 0. Since the customer service time is at least 80 seconds, only groups of timestamps which represent a time interval of at least 80 seconds with velocity equal to 0 are added to S. On the other side, it is noticed that a temporary stop during the ride rarely lasts longer than 40-50 seconds, so with this approach stops during traffic jams or red lights are discarded.

The customer data sequence C_i is given as a sequence of coordinates (x_i, y_i) in order in which the vehicle should serve them. Assigning stops to customers is the topic of the next section.

A. *Assigning stops to customers*

Before the implementation of any kind of method, the coordinates of a 100 customers were tested manually. It was determined that some of the coordinates were not correct, as shown in the Table I, and that it was necessary to correct them. In order to do that, the following approach was used; after identifying the set of stops S, some of them are assigned to customers, based on the distances between them and the stops.

TABLE I: LOCATION ERROR

Range of error	*Percent of customers*
< 10 m	43%
< 30 m	77%
< 200 m	96%
> 200 m	4%

A stop is assigned to a customer if the distance between the stop and the customer is less than 50 meters. If at the end of the day it is confirmed that the route was successfully completed and that there exists a customer to which none of the stops were assigned, that customer gets sent to the workers in order for them to check his coordinates. In that way the coordinates are being corrected step by step, therefore lowering the number of customers with incorrect coordinates. Also, if it is determined that a vehicle, while visiting a customer, always stops approximately at the same location which is more than 20 meters away from the customer, then that customer's coordinates get corrected to a new value which is equal to the centroid of the previous stops.

B. Prediction of service times

As it was previously mentioned, every customer has a time interval in which he is available for the shipment serving. It is of great importance for the successful work of the algorithm that the time calculations needed for the drop off of the shipment to the customer as well as the time needed to get from one customer to another are correct. In the first version of the algorithm, the time spent with the customer was calculated by a simple formula, $10 + \frac{n}{2}$ minutes, where n is the number of articles in the customer's order. Later, the formula was changed to keep count of the weight and volume of the articles, which lead to some improvement. However, it has been noticed that the time spent with the customer depends mostly on the sole customer, that is on the environmental surroundings, whether there is free parking space as well as the efficiency of the workers. That way, it was noticed that for some of the customers the approximation of the time spent with them was usually shorter than it really is, while with other customers it was usually longer.

As the errors were created due to the false calculations of the fixed time spent with the customers and not by the sole drop off of the articles, the way in which those calculations are computed was changed. The time approximation for the article drop off showed to be quite good, and so that time was deducted from the total time which the vehicle spends with the customer. In that way, the time that the vehicle spends with the customer, not including the sole article drop off, is obtained. That is in fact the time needed for the vehicle to approach the customer, park and the impact of the efficiency of the worker on that time (e.g. paperwork). In the end, in order to get the best result, the time is approximated with the average of previous times the vehicle spent with customers.

Aside from the approximation of time spent with the customer, some smaller mistakes were observed during the time needed to get from one customer to other. Of course, some minor mistakes are expected, but it turned out that the approximations on some stocks were constantly bigger than the real time the vehicle spent travelling, while on others they were constantly smaller. In order to fix that, while doing the time approximations, the time that was previously spent while travelling between some two customers is always being considered.

C. Other improvements

The company for which the algorithm was built wanted to be able to control the workers and track their efficiency. It was not a rare event that some vehicles don't even arrive to some customer in the provided time interval or that they don't get to deliver all of the orders.

By checking those cases, it was found that the reason for those failures of shipment are mostly due to the negligence or disobedience of the worker, who spends too much time on his break or doesn't respect the customer serving order which the algorithm provides. In some rare cases problems arose due to bad time approximation of the drop off or unforeseen circumstances (e.g. traffic jams due to car accidents).

IV. RESULTS

The vehicle tracking system which is described is implemented in one of the largest distribution companies in Bosnia and Herzegovina.

The approximation of the customers service times is tested in a real-world scenario. It is compared with real service time and previous approximations. For each of the 25 customers, sequences of 10 stops are analyzed. Previous approximations, new approximations and the real values of the service times are compared. Those values for one of the customers are shown in Fig. 2.

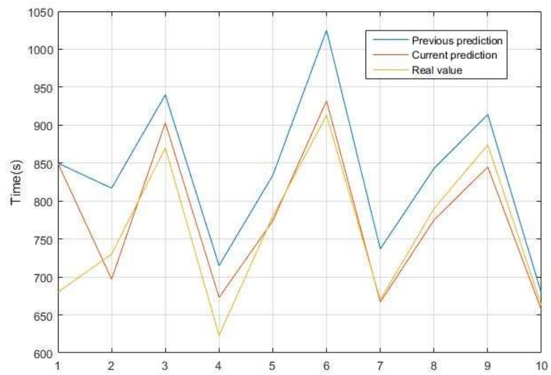

Fig. 3. Comparison of approximations for service time of customers

As expected, as more service times are taken into account new approximations get closer to the real service time. The error margin of the new approximation value is about 5% on average, while the error margin of previous the value was about 12% on average. So, the error margin decreased by more than two times.

However, for a small number of customers the new approximations are not significantly better than the old ones. This happens generally to customers whose order shipment happened to be crowded, that is the vehicle had to wait in line, behind other shipment vehicles, in order to drop off the articles to the mentioned customer. For this type of customers, service time depends on many factors which are hard to predict, like moving of other shipment vehicles.

The distribution company in which the system was implemented had more than 15000 customers. After 4 months of improving the coordinates the test was finally executed. Again 100 customers were randomly chosen and the location error for them was manually checked. It was found that the error in location for 62 of them was less than 10 meters, for 89 of 100 it was less than 30 meters, and for 99 of 100 it was less than 200 meters. So, the precision of the customers' locations significantly improved, and in the future they should be even better.

Improving the approximations of service times and precision of coordinates of the customers had a large impact on the performance of the VRPTW algorithm. Before implementing the methods described in this paper, there were situations in which drivers followed the planned route, but due to incorrect input data, did not return to depot in the scheduled time.

TABLE II: ERROR OF PREDICTED RETURNING TIME

Range of error	***Before***	***After***
< 15 min	27%	45%
< 30 min	49%	62%
< 45 min	57%	71%
< 60 min	69%	87%

More than 200 routes in which the driver visited all customers in the right order are being considered. The difference between the scheduled returning time and the real returning time to the depot significantly decreased after implementing the described methods (table II).

V. CONCLUSION

As large companies provide their services to many customers, who are often scattered on larger areas, rather than smaller ones, an enormous amount of money is spent on fuel. In order to save money, it is very important for those companies to spare as much fuel as possible, that is to optimize the transport of the customer's order. The transport optimization problem is a very hard one, which is still being researched today in various forms, like the previously mentioned one including the customer's time windows.

However, the thing that makes this optimization problem even harder is the fact that it is not easy to get the correct input data for the algorithm, like for example the time needed to get from one customer to another or for serving one customer. Sometimes it even happens that, due to the human factor, some customer's location coordinates are not entered correctly.

Here the techniques for solving these problems are described. They have improved the input data needed for the algorithm and as a consequence of that the algorithm itself gave better results. In that way better approximations were created in regards to when the vehicle will arrive at the customer's location and how long it will stay there, which in the end resulted in a significantly lower number of customers whom the vehicle did not succeed to visit.

By implementing the neural network, it is intended to even further improve the approximation of the time spent dropping off the shipment, because it is clear that the time needed for that depends on the structure of the articles. Also, the intention is to use the neural network for a better approximation of the time needed to get from one customer to another. However, for two fixed customers, it is rare for the vehicle to go directly from one to the other which means that the neural network wouldn't have enough data to improve those approximations. That is why checkpoints should be created on locations through which the vehicles have to pass in order to get to the customer, as well as on road intersections. The distance between the checkpoints would be calculated using the neural network (if there is enough data). It is clear that this way a vehicle will often travel between two neighboring checkpoints and that there will in general be enough data for the neural network to work. However, some problems arise because during the approximation of the time spent between two customers, errors accumulate between the checkpoints that are in between those two customers and in that way many of those little errors can lead to a bigger one in the total calculation.

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