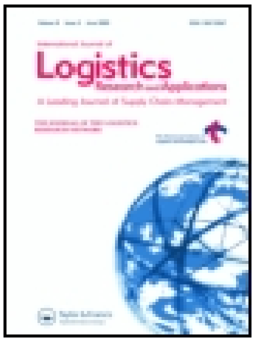

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The impact of traffic congestion when optimising delivery routes in real time. A case study in Spain

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ABSTRACT

This paper studies the importance of considering congestion costs when optimising delivery routes. Through the analysis of two study areas (the region of Catalonia and the city of Barcelona, in Spain), four different scenarios have been implemented and compared in which different objective functions are minimised: Euclidean distance, real distance, real time with static congestion, and real time with dynamic congestion. The data have been collected from Google Maps, which allows us to obtain information on traffic conditions in real time. The results indicate that minimising real time considering congestion as a dynamic attribute which varies throughout the day is the most efficient method to optimise delivery routes, especially within urban areas. For the two study areas, and using this dynamic approach in which real-time congestion costs are reflected into the vehicle routing problem, savings in time up to 11% have been obtained.

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Vehicle routing problem; logistics; congestion; real-time; Google Maps; smart cities

Introduction

Transport and logistics (T&L) activities are a key sector for worldwide economies, as they contribute to the economic and social progress of modern societies. The modelling and optimisation of vehicle routing problems (VRP) is one of the recurrent topics existing in the literature related to T&L. Traditional VRP problems consider fleets with different configurations (Heterogeneous Fleet Vehicle Routing Problem – HFVRP), with time windows (Vehicle Routing Problem with Time Windows – VRPTW), or with different distribution levels (Two Echelon Vehicle Routing Problem – 2E-VRP). Moreover, the new problems also take into account the use of electric vehicles (EVRP), for which the driving range is the main constraint. However, these solutions have been commonly applied at a strategic level, minimising a distance-based cost function and ignoring certain variables such as congestion or drivers behaviours (Srivatsa and Gajanand 2017).

In the last decade, traffic congestion has exponentially increased, especially in dense urban areas, (Börjesson et al. 2015), and according to the United Nations (2015), 70% of the world's population will live in cities by 2050, putting increased strain on urban infrastructure and transport systems. In parallel, big cities and regions are becoming smart, boosting initiatives and new projects in order to enhance their efficiency and sustainability (Lyons forthcoming). In contrast, on-demand deliveries such as Amazon, Deliveroo, or JusEat are changing the way people understand logistic activities within urban areas. It is becoming more frequent that the product demand, the driver availability, the mode of transport (bike, tricycle, electric vehicle, or drone in a future scenario), and their position in the map is not known in advance, increasing in this way the uncertainty associated to transportation data. In these cases, where local conditions are in constant change, the application of

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traditional VRP problems – and therefore, the strategic planning process – becomes inappropriate. Therefore, it seems plausible that new approaches were needed to improve the way in which VRPs are applied, especially within urban areas, designing new perspectives to consider different dynamic and stochastic aspects in transport such as traffic congestion or driver behaviour.

In light of the aforementioned ideas, this paper is intended to analyse the importance of considering real-time congestion costs into the VRP. Therefore, the potential benefits of incorporating congestion in terms of cost savings are shown. For this purpose, a dynamic VRP approach is presented in which real-time data, obtained from Google Maps, are applied within the optimisation algorithm in two study areas: the region of Catalonia and the city of Barcelona, in Spain.

Literature review

The VRP is, undoubtedly, one of the most relevant topics presented in the transport and logistics literature (Eksioglu, Volkan, and Reisman 2009). It was in 1954 when the first solution of the Traveling Salesman Problem appeared (Dantzig, Fulkerson, and Johnson 1954). Since then, a large number of algorithms have been developed in order to optimise delivery routes. One of them that should be highlighted is the Clarke and Wright Algorithm (Clarke and Wright 1964), which is able to solve a problem where a heterogeneous fleet of trucks is used to make products distribution from a central depot to some delivery points. Over time, different versions of the VRP appeared and were applied to different fields, such as fleet routing (Levin 1971), bus routing (Wilson and Sussman 1971), or waste collection (Liebman 1970). However, the first time the words 'vehicle routing' were shown together was in the title of a research work written in 1977 by Golden, Magnanti, and Nguyan (1977).

Over the last 40 years, as explained before, some variants have been introduced in order to add complexity and more realism to the problem, such as the capacitated VRP, the VRP with time windows (VRPTW) (Chiang, Lin, and Hsueh 2004), the split delivery VRP (Wang et al. 2013), the heterogeneous fleet (HFVRP), the periodic deliveries VRP, or the Pickup and Delivery VRP (Jung and Haghani 2000). Furthermore, taking into account the increasing development of electric vehicles, new approaches have appeared, being one of them the Green VRP (Figliozzi 2010), in which the range of the vehicle according to its battery duration is considered. Nowadays, new variants of the VRP are being implemented using drones or autonomous vehicles (Azevedo et al. 2016) which will improve the distribution of goods within urban areas. However, the number of publications in these fields is still scarce.

It is important to note that the study of more realistic VRP applications was limited due to the required computational effort, and it was not until the 1990s when the introduction of metaheuristics into the field of VRP applications allowed for more complex problems to be solved. Besides this, simheuristics, which combines the power of simulation with optimisation algorithms, has made it possible to solve realistic models that also includes, for example demand uncertainty (Juan et al. 2015). Nevertheless, according to Srivatsa and Gajanand (2017), who made a review of the VRP evolution over time, the approaches used to solve this kind of logistic problems can be reduced into four chronological stages: VRP with distance minimisation, VRP with time minimisation, VRP with fuel minimisation, and VRP with pollution minimisation. In spite of the improvement of the algorithms and the apparition of new VRP variants, the truth is that most of the previously considered approaches (even the ones in which time was minimised) were based on or related to distance.

In the literature, the concept of cost minimisation often refers to optimising the distance travelled or minimising penalty costs for violating time windows, depending on the context (Dantzig and Ramser 1959). Regarding the fuel consumption and pollution minimisation (Bektas and Laporte 2011), the aforementioned approaches have marked an important turnaround in the VRP with the objectives focus on managing economic and environmental costs (Kara, Yetis, and Kadri 2007). As for time minimisation, the approach is similar to the distance minimisation with the exception that total travel time is optimised instead of distance (Donati et al. 2008). In this case, congestion has been sometimes considered but through a probabilistic perspective, and therefore, it may not be realistic when congestion effects are relevant.

However, as far as city logistics is concerned, the classical routing problem and its variants do not fit to perfection to provide good results. As stated by Alvarez et al. (2017), the research community has ignored the influence of congestion for decades while scholars were mainly focusing their attention on the application of VRP at a strategic level, with the distance-based cost functions as a main concern. According to this, some researchers have shown their interest in the field over the last few years. For example, Conrad and Figliozzi (2010) integrated historical traffic data from the Portland Oregon Regional Transportation Archive Listing (PORTAL) with the Google Maps API for the implementation of the Time-Dependant VRP in Portland (Oregon). Other examples of integrating historical data are given by Kim et al. (2016) and Huang et al. (2017). The former made use of real data from the Land Transport Authority to solve a real case in Singapore employing the Google Maps API, and the latter introduced the 'Path Flexibility' concept. This term consists of the consideration of path selection in the time-dependent VRP as an integrated decision according to the traffic congestion. Although the use of data from Google Maps for transport-related studies is common, as seen in the section 'Using data from Google', their use together with route optimisation processes is relatively new.

Nha, Djahel, and Murphy (2012) mixed the power of traffic simulation with traditional VRP solvers, being the first to create this mixed methodology according to the authors' knowledge. Similarly, these authors used the SUMO software in order to simulate solutions obtained by different VRP algorithms, although they did not contrast their results with real data. Later, Jiang and Mahmassani (2014) made a step forward by using historical traffic data to introduce them into the simulation software DYNASMART, being pioneers in taking real congestion costs into account inside a VRP model. Finally, Lai et al. (2014) wrote about the importance of new technologies and Intelligent Transport Systems in order to measure congestion costs to apply them into the route optimisation algorithms, but the approach was not practical and no real data were used.

Summing up, most of the previous analyses show clear limitations. Thus, some of those studies are based on managing historical traffic data instead of using real-time data. Others are biasly focused on simulation but without considering real data, and a few of them talk about the use of real data but using a purely theoretical approach which is difficult to implement in a real case. Therefore, new approximations are needed to consider congestion effects within the VRP arena.

Methodology

In order to understand the importance of considering congestion when solving VRP problems, four scenarios of increasing complexity have been developed. Studying the differences between these scenarios will make it possible to understand how important congestion is for the VRP.

Scenarios

These are the four scenarios that have been analysed.

Scenario 1 (S1): minimising Euclidean distance

The traditional route optimisation has been developed by minimising distances, specifically Euclidean distances (Paessens 1988). Thus, this approximation requires the knowledge of the all network node coordinates in order to calculate their reciprocal distances. However, let us consider a real trip through any region or city. It is clear that the Euclidean distance is not the one covered by a person who moves from one point A to another point B, but there is a real network topology which is the main constraint to be taken into account. Therefore, it can be said that the ratio between the Euclidean distance and the real distance (Network Topology Factor) is not always equal to 1. Therefore, it is important to consider this uneven situation when optimising routes in order to get efficient and realistic results.

Scenario 2 (S2): minimising real distance

The second scenario makes use of the real distance instead of the Euclidean distance. For this purpose, it is required to have access to road maps so that the real distance between two points can be calculated considering the real topology of the network. Although Scenario 2 is more realistic than Scenario 1, its main limitation is that the congestion effect is not considered. When a route from point A to point B is designed, sometimes the shortest route from point A to point B is congested, so people may decide to choose a route that is a bit longer but that requires less time. Therefore, distance is not the only variable to consider in real life when it comes to choosing the route, but also travel time and congestion effects. This situation explains why Scenario 3 and Scenario 4 are needed to improve the accuracy of the solution.

Scenario 3 (S3): minimising real time (static congestion)

This scenario diverges from the previous approaches in the use of real-time information to make decisions and shows the importance of considering congestion effects in the road network. In this case, it is required to have access to real-time data (sometimes merged with historical data) on the traffic conditions in the road network. This information can be provided by Google Maps for example, but it can be also taken from traffic sensors within smart cities that make use of Big Data technologies. This approach can be a correct approximation when the travel time is not too long and when congestion costs remain unchanged throughout the route. However, if the route takes some hours to be completed, it is easy to understand that extrapolating congestion data from the starting hour to the rest of the hours in which the route takes place is not realistic, as congestion changes significantly during the day. Therefore, a dynamic approach is needed.

Scenario 4 (S4): minimising real time (dynamic congestion)

Unlike Scenario 3, this last scenario considers the variability in congestion during the day, giving a more realistic solution. The main contribution of this approach is that congestion – and therefore, the route – is being updated with real-time information every time the truck reaches a new client. As in Scenario 3, this approach requires to have access to real-time information, not just for the starting time of the trip, but during the whole route. This information can be also obtained using data from Google Maps. As commented before, these data could be also obtained using other sources of data, for example using data from traffic sensors from the city council uploaded to an online database.

Process

The process required to develop these four scenarios is as follows. Firstly, the road network is modelled based on the real road links of the studied area for which all the important junctions and links have been considered. For this purpose, the software QGIS has been used. More details will be shown in the next section. Secondly, all the necessary inputs to be used within the optimisation process have been already obtained. For Scenario 1, Euclidean distances and coordinates are directly extracted from the GIS model. As for the other scenarios, a process using JAVA has been developed in order to subtract the necessary information (real distance and real time) from Google Maps (the Google Maps API or other data sources could be also used). Finally, once all the inputs have been extracted, the optimisation process takes place. The algorithm has been developed in JAVA and Visual Basic, and it consists of five different steps:

1. Generation of a new instance of depot/customers randomly assigned within the road network using a Visual Basic program. Different parameters can be set (truck capacity, number of clients, starting time, etc.) in order to take stochasticity effects into account.

2. Then, the origin–destination (OD) matrix (Euclidian distance, real distance, or real time) is generated and used by the Dijkstra algorithm (1959) to obtain the costs between the depot and all the customers.
3. Now, the Clarke and Wright Savings algorithm (CWS) (1964) is implemented in order to obtain the best preliminary solution that CWS heuristic is able to achieve.
4. This solution is the initial solution for the Tabu Search algorithm, which is run to improve the preliminary solution. This metaheuristic guides the local search heuristic algorithm to explore the space of solutions beyond local optima. To do so, a flexible memory is implemented based on Taillard's method (2016), where some previous movements are saved to avoid them during a number of iterations.
5. The final solution is obtained and the route is saved together with the time needed, distance travelled, and links used, and step 1 is repeated in order to run another instance. This will allow to obtain a sample size of solutions that is big to perform the statistical analysis and to obtain realistic results taken randomness into account.

Figure 1 shows the whole process commented above, which has been implemented using Visual Basic and JAVA. This approach allows two modes of operation: (1) selecting the current time or (2) selecting a future starting time. In both cases, Google Maps makes use of real-time data complemented with historical data to forecast the future traffic conditions.

Using data from Google

Traditionally, transport practitioners have obtained transport data from direct observations, using a broad range of techniques such as roadside interviews, traffic counts, or speed measurements (Department for Transport (DfT) 2007; Ortuzar and Willumsen 2011). However, the cost of obtaining this information for extensive areas together with the sampling error existing in the data (Tolouei, Abellan, and Alvarez 2016) is one of the main limitation that has led transport planners to start testing other approaches with which they could obtain more reliable traffic information that could also allow for updating the transport models with real-time information (Catapult Transport Systems 2015).

Over the last years, technology improvements, in particular those related to mobile phones, Bluetooth, or GPS-enabled devices, have shown the possibilities of more extensive, accurate, and less

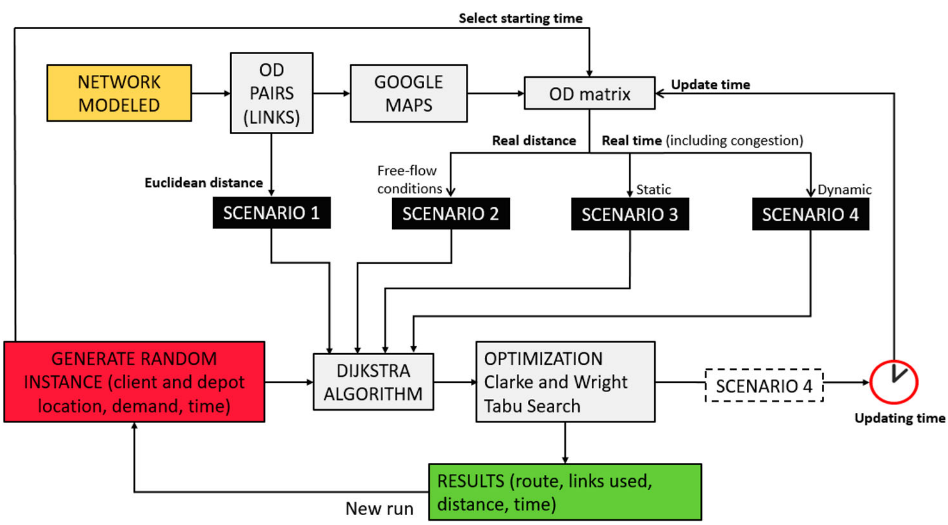

Figure 1. Diagram showing the process implemented to generate different scenarios.

expensive sources of data to be used to model urban transport (Bureau of Infrastructure, Transport and Regional Economics (BITRE) 2014). Therefore, some researchers have started to make use of data from Bluetooth sensors (Thogulava, Antonov, and Bingham 2015) or data from mobile phone operators (Lehan and Gross 2016) when building transport models and applications. Although these methods have been shown to be valid for transport modelling purposes (Tolouei and Alvarez 2015), they are not that efficient when it is needed to obtain the travel time and congestion for each link of a whole network, as their data are usually limited to a specific area (in the case of Bluetooth sensors), or do not show information for each link, but aggregate information for zones (in the case of mobile phone data).

As commented in the literature review section, Google Maps data are being used by researchers and practitioners to obtain information on travel times and congestion. The validity of data from Google has been demonstrated in different studies, showing that real-time travel times obtained from Google Maps are relatively accurate, especially within large urban areas (Zhao and Spall 2016; Sana, Castiglione, and Cooper 2017; Rahmani, Koutsopoulos, and Jenelius 2017).

Therefore, for this research study, data from Google Maps is thought to be accurate and easy to implement. However, it is important to mention that the aim of this paper is not to demonstrate the validity of data from Google, but the importance of considering congestion as a dynamic attribute within the route optimisation process. That means that other sources of data, such as traffic data from sensors within smart cities or floating car data, could be used for the purpose of this research.

Case studies

The methodology has been applied to two real cases in order to understand to what extent congestion affects routing at regional and urban levels. In both cases, data from Google Maps is thought to be more accurate than in other small cities due to the high level of traffic and the higher sample size (see 'Using data from Google' section).

The first case (regional) is focused on the region of Catalonia, Spain, with a population of about 7.5 million of people (Instituto Nacional de Estadística (INE) 2017). This area has an important logistic activity where over 60% of the exported freight is transported by road (CIMALSA 2017), and it has been considered as a suitable region for this study due to the high levels of congestion existing throughout the region in comparison with other areas in Spain (also caused by through traffic to/from France), together with the importance this area has for the Spanish economy. The road network of Catalonia has a length of 12,000 km, and it has been modelled in QGIS with a high level of realism considering the main freight routes. In total, 92 nodes and 342 links have been modelled, as shown in Figure 2 (left).

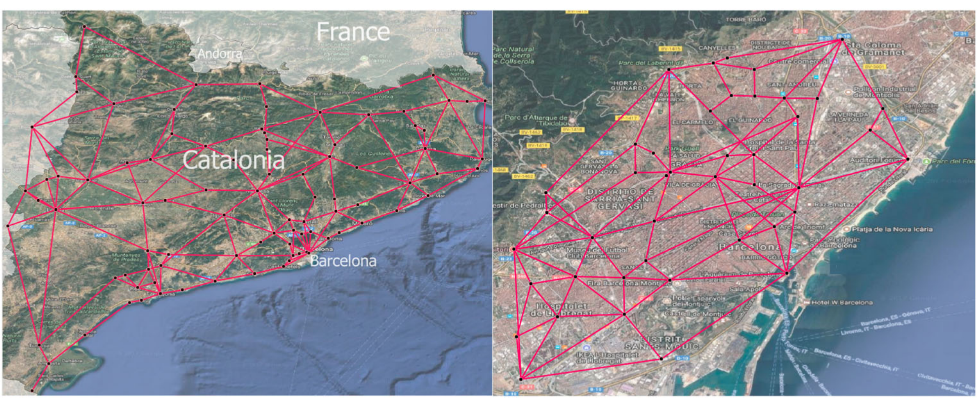

Figure 2. Networks modelled showing the cases of Catalonia (left) and Barcelona (right). Source: Google Maps.

The second case (urban) corresponds to the city of Barcelona, with a population of 1.6 million. Although the number of heavy goods vehicles trips within Barcelona has decreased in the last years, 6% of the total traffic still consists of trucks and vans (Barcelona City Council 2017). The modelled network in QGIS (Figure 2, right) is composed of 43 nodes and 197 links, and it has been modelled considering the main freight routes within the city as well as the real restrictions and bans existing in some of the local roads.

Analysis of the results

Each of the four scenarios mentioned before have been run 30 times for every hour of the day (route starting time), and for both models: Catalonia (regional) and Barcelona (urban). Therefore, 5760 instances (30 runs × 24 hours × 4 scenarios × 2 models) have been automatically generated which is thought to be enough to obtain representative results taking stochasticity effects into account. In each run, 10 clients and 1 depot are randomly assigned within the road network using a uniform distribution U[0,1], and the client demand is also randomly generated (U[0,1]). For this study, the truck capacity has been set to 50 units. Although the results shown here correspond to data from a Monday in June 2017, Google complements the accuracy of the data with historical data; therefore, the data is thought to be representative for a neutral day.

For each link within the network, and for each model, the attributes defined as Euclidean distance, real distance, and real time have been obtained as indicated in Figure 1. During the optimisation process, one of these attributes has been minimised depending on the scenario. The study of the relationship between these attributes for all the links within the network also allows us to understand that, as seen in Table 1, the correlation between real distance and Euclidean distance is stronger at a regional level than at an urban level. The network topology factor (Euclidean distance over real distance) also suggests this assertion. When real distance is correlated with real time (for each hour of the day), the coefficient of determination (R^2) is also higher at a regional level and it varies throughout the day. These results show that the solutions obtained when minimising Euclidean distance, real distance, and real time will differ, and these differences will be greater at an urban level. Therefore, these preliminary results indicate that network topology and real time (including congestion) are factors that should be taken into account when optimising delivery routes, especially within urban areas.

The model results for the region of Catalonia are shown in Figure 3. The chart indicates the total travel time needed to complete the route for every starting time. It can also be seen how the total travel time varies during the day as a result of the real congestion, with the AM and the PM peaks experiencing higher travel times. It can be seen how minimising the Euclidean distance (Scenario 1) is the least efficient method to optimise the route, as the time required to complete it is the highest one. This situation is due to the fact that the real network topology is not being considered, and in real life, the truck driver does not travel using crow-fly distances but real roads. When real distances are being minimised (Scenario 2), the total travel time tends to be reduced by 1.5% on average when comparing it with Scenario 1. This method is more efficient as the real road network is considered so the optimisation approach is more realistic. On the other hand, Scenario 3 takes congestion into account, so the results improve by 3.4% on average if when comparing them with Scenario 2 (4.4% during the peaks). Therefore, optimising routes taking congestion into consideration leads to better results and time savings.

So far, changes in congestion levels during the route have not been considered and, as shown in the chart, congestion is higher during the AM and PM peaks. Therefore, the travel times shown in

Table 1. Network attributes for the Catalonia and Barcelona models.

	Catalonia	Barcelona
R^2 (real distance – Euclidean distance)	0.91	0.74
Network Topology Factor	0.73	0.65
R^2 (real distance – real time)	0.80–0.86	0.57–0.70

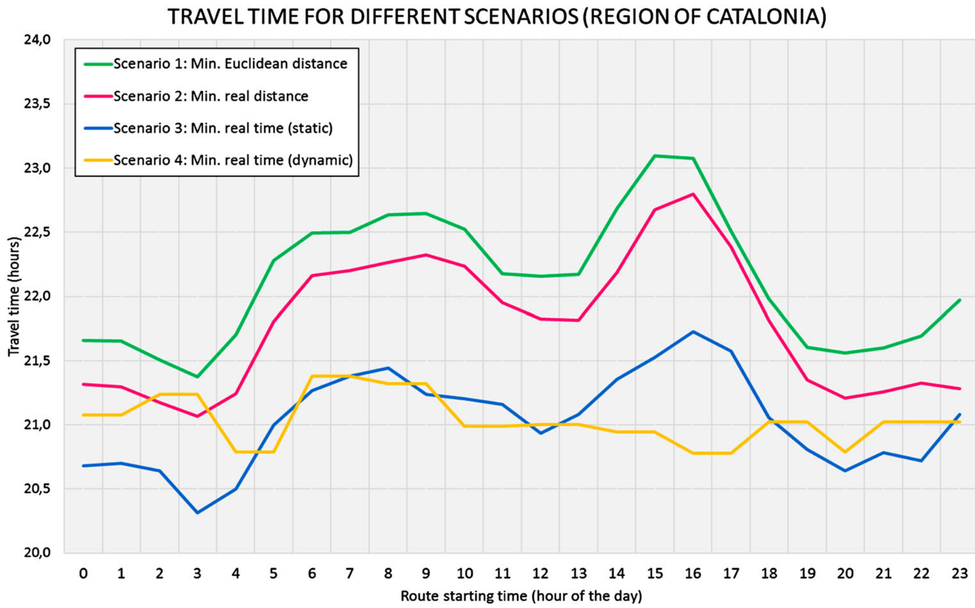

Figure 3. Model results for the region of Catalonia.

Scenarios 1, 2, and 3 are not realistic as they do not consider the dynamic conditions of traffic and congestion. For example, if the route starts at 8 AM, all the costs (travel times) for the links during the whole route corresponds to the ones at 8 AM, even though the route takes up to 21 hours to be completed which means that costs (travel times) should be changed. Scenario 4 deals with this problem as congestion costs are being updated every time a new client is reached, so the rest of the route is replanned accordingly, and the results are more realistic.

Therefore, results show, for the region of Catalonia, that minimising real time to consider congestion effects leads to more efficient results when delivery routes are optimised. However, the use of static congestion costs instead of dynamic can lead to misleading results. As an example, let us consider that a logistics company is planning a delivery route. If they used the approach from Scenario 3, they would understand that starting the route at 3 AM is better than starting it at 4 PM, so the company might decide to start the route then. However, in real life, they will not be using congestion costs from 3 AM during the whole route, so they will not be able to get the route done in less than 20.5 hours as estimated in Scenario 3. Therefore, Scenario 4 is more appropriate as dynamic traffic conditions are being considered. If the decision-maker applies the approach from Scenario 4, the travel time will remain almost constant no matter which time they start the route at, as the route takes about 21 hours to complete, and the driver will be travelling (in both cases) during AM and PM peaks. Nevertheless, the order of the customers in the route will vary.

As shown in Figure 4, similar results are obtained for the city of Barcelona. In this case, minimising real distance (Scenario 2) instead of Euclidean distance (Scenario 1) to optimise delivery routes is also better, as the time savings are about 1.5% on average, similar to the ones obtained for the region of Catalonia. When time is minimised (Scenario 3), the results improve by 4.46% on average (5.2% during peak hours) in comparison to Scenario 2. These savings obtained in Barcelona are greater than the ones from Catalonia, and this difference may be related to the fact that, due to the congestion, time and distance are less correlated at a city level than at a regional level (as stated in Table 1), so the optimisation approach becomes more efficient in Barcelona.

Results from Scenario 4 in Barcelona are slightly different from the ones in Catalonia, because the route here only takes about 4 hours to be completed (instead of 21 hours), so the starting time does

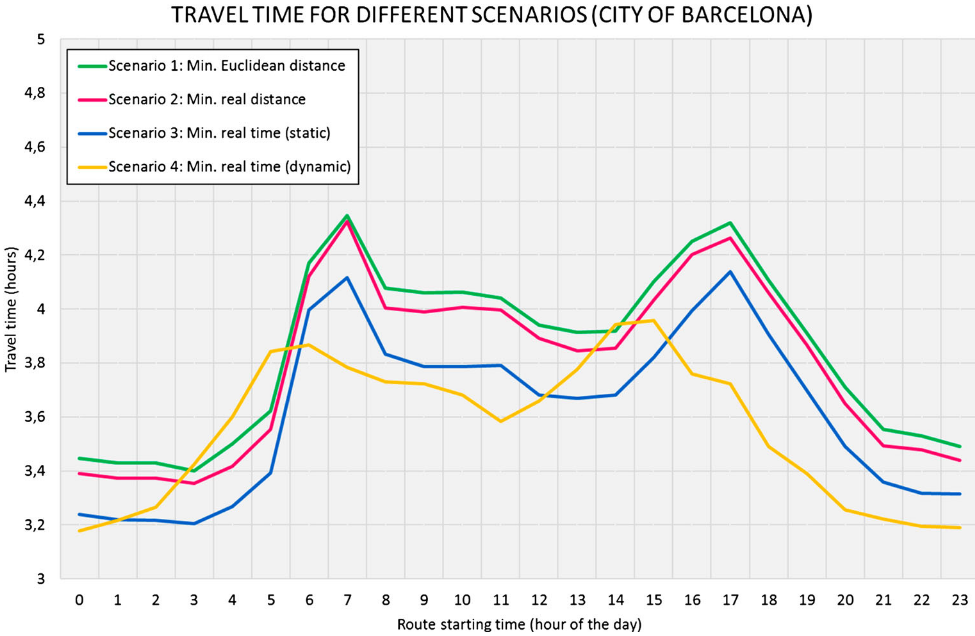

Figure 4. Model results for the city of Barcelona.

become an important factor to consider in order to avoid congestion during peak hours. Following with the previous example, if the logistics company wants to plan a delivery route using the static approach from Scenario 3, the planner could decide to start it at 3 AM. However, the dynamic approach from Scenario 4 which is more realistic indicates that it would be better to start the route at midnight, as the driver would avoid the AM peak. The same occurs in the PM peak. Using the static approach, they should avoid starting the route at 5 PM, and the planner could think that leaving at 2 PM would take us less time. However, the dynamic approach shows that leaving at 2 PM would not be advantageous as the driver had to travel during the PM peak when congestion is increasing. In this case, starting the route at 5 PM, when the congestion is about to start to decrease, would be a more efficient option.

Table 2 shows the differences in travel time and travel distance between Scenario 4 and the rest of the scenarios studied. It can be seen that the approach from Scenario 4 gets lower travel times than the rest of the scenarios. Although the solution using the dynamic approach is also suitable for Catalonia, the efficiency of this dynamic approach is higher when it is used within Barcelona, especially during peak periods. In this case, the travel time decreases by 6% in comparison to the approach from Scenario 3 (minimising time with static congestion), 9.9% in comparison to the approach from Scenario 2 (minimising real distance), and 11% if compared with the approach from Scenario 1 (minimising Euclidean distance). As for travel distances, using the approach from Scenario 4 implies that, for the case of Catalonia, travel distances

Table 2. Differences in travel time and travel distance for each scenario and model.

	Region of Catalonia				City of Barcelona			
	Diff. travel time		Diff. travel distance		Diff. travel time		Diff. travel distance	
	Overall	Peaks	Overall	Peaks	Overall	Peaks	Overall	Peaks
S4 vs. S3	0.0%	−0.8%	6.0%	1.5%	−1.1%	−6.0%	−5.7%	−5.7%
S4 vs. S2	−4.3%	−6.3%	9.4%	4.9%	−5.6%	−9.9%	1.4%	1.2%
S4 vs. S1	−2.9%	−5.1%	8.0%	3.6%	−7.0%	−11.0%	−5.0%	−5.0%

increase due to the rerouting needed to avoid congestion. However, for the peaks, the savings in travel times are greater than the increase in distance, i.e. the truck drives more kilometres but it saves more time. For the case of Barcelona, the dynamic approach from Scenario 4 also leads to reductions in distance travelled (overall and for peak hours) if compared with Scenario 3 and Scenario 1. It makes sense that the distance travelled in Scenario 2 (minimising real distance) is lower than in Scenario 4, but the travel times are higher.

In general, the results shown in this section have indicated that minimising times considering congestion effects instead of minimising distances is the best approach to optimise delivery routes, especially within urban areas and during peak periods. Furthermore, it has been demonstrated that taking congestion as a static attribute may lead to incorrect or unrealistic results. Therefore, a dynamic approach (as the explained in this paper) is needed in which congestion costs are updated in real time, for example every time the truck reaches a client, through the use of data from Google Maps, the Google Maps API, or from another platform. As observed in this section, this approach could lead to time savings up to 11% during peak hours.

Discussion and conclusions

This paper has presented a new methodology in which a dynamic time-dependent VRP has been used to optimise delivery routes taking traffic congestion into consideration. Traffic congestion data have been collected from Google Maps. In order to compare the results of this approach with previous existing methods, four different scenarios have been set and applied to two different models: the region of Catalonia and the city of Barcelona, in Spain.

Results have shown that minimising real travel time, which includes congestion and the real network topology, instead of distance (real or Euclidean distance) leads to more efficient results. Applying this dynamic approach, time savings up to 11% are obtained for the city of Barcelona if compared with the approach in which just real distance is minimised. These results also indicate that, against what is traditionally thought, congestion affects routing not just at an urban level but also at a regional/strategic level. This means that ignoring congestion when optimising delivery routes will lead to inefficient results that will increase the costs of the logistic operations and, therefore, the costs of the final products.

Nowadays, planning delivery routes in advance is gradually becoming more inefficient as by doing so dynamic local conditions are being ignored. Although it is certainly possible to only use historical data (even from previous days) when planning the route, this situation would not be appropriate when other important aspects that may affect routing such as accidents, road closures, or change in traffic conditions need to be considered. Moreover, with the increasing level of urbanisation that our cities are experiencing, congestion is becoming a major issue for logistics companies that need to do the last-mile delivery. Also, the boost of online shopping and on-demand deliveries highlights the change that the route planning process is undertaking: from the traditional methodology in which routes were planned in advance to the current trend in which the route has to be set in real-time and become adaptive.

The analysis here presented offers an improvement to create delivery routes that are more realistic and efficient which, in the end, lead to cost savings. The algorithm used here is flexible as different traditional variants to the VRP (such as time windows, driver availability, or a fleet with different vehicles) can be implemented. Also, this paper could be seen as part of a new line of research in which the traditional approaches of the VRP are giving rise to new perspectives focused on smart cities where traffic sensors and Big Data technologies are being used to track the traffic conditions (and even the client demands) in real-time in order to adapt the routes to the dynamic conditions that exist in the cities. Logistics is not the only field that could benefit from this approach, but also emergency services and waste collection services, among others.

There is also room for improvement here. As mentioned in the results, this methodology reduces the travel time but sometimes increases the distance travelled (due to rerouting). Some people could wonder then whether saving time is less or more expensive than saving distance, and what the trade-off between these two costs is. Therefore, it would be possible to use this dynamic approach but by minimising a cost function based on both distance and travel time through the use of the operating cost of the vehicle (related to distance), and the cost/value of time. By doing this, congestion costs would be considered together with distance costs. The results using the mentioned approach could be of a higher interest for logistic companies. Similarly, it could be possible to adapt this methodology to be used together with micro- or macro-traffic simulation software in which different variables such as distance, time, pollution, or noise can be analysed together.

Logistics companies have to be adapted to this new era where planning in advance is becoming obsolete. New approaches, like the one proposed in this paper, need to be in place to be able to compete in a market that is increasingly becoming more complex and fierce. In a world in which our cities are becoming smart, the tools we use to plan delivery routes also have to be.

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