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# Sustainable Urban Delivery: The Learning Process of Path Costs Enhanced by Information and Communication Technologies

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**Abstract:** Today, local administrations are faced with the presence of greater constraints in terms of the use of space and time. At the same time, large amount of data is available to fleet managers that can be used for controlling their fleets. This work is set in the context defined by sustainable city logistics, and information and communication technologies (ICTs), to formalize the three themes of the smart city (transport, ICTs and energy savings) in a single problem. Following this, the main purpose of the study is to propose a unified formulation of the basic problem of fleets, i.e., the traveling salesman problem (TSP), which explicitly includes the use of emerging information and communication technologies (e-ICTs) pointing out the learning process of path costs in urban delivery. This research explores the opportunity to extend the path cost formation with a within-day and day-to-day learning process, including the specification of the attributes provided by e-ICTs. As shown through a real test case, the research answers to queries coming from operators and collectivities to improve city liveability and sustainability. It includes both economic sustainability for companies/enterprises and environmental sustainability for local administrations (and collectivities). Besides contributing to reduce the times and kms travelled by commercial vehicles, as well as the interference of freight vehicles with other traffic components, it also contributes to road accident reduction (social sustainability). Therefore, after the re-examination of TSP, this paper presents the proposed unitary formulation and its benefits through the discussion of results obtained in a real case study. Finally, the possible innovation guided by e-ICT is pointed out.

**Keywords:** city logistics; smart city; knowledge management; urban delivery; internet of things; big data; learning process; path cost; within-day dynamic; day-to-day dynamic; city sustainability; city livability; delivery costs



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## 1. Introduction

In Europe, about 69% of road accidents occur in cities and 25% of the $CO_2$ transport sector emissions come from urban transport (Cattaruzza et al. [1]; Ranieri et al. [2]). In addition, more than half of the freight transported by trucks is moved below 50 km, and more than three quarters under the 150 km of distance (White paper [3]; Russo and Comi [4]). Therefore, the relevance of reducing urban transportation impacts and increasing sustainability emerges for people, public authorities and enterprises. Given that the transportation impacts, as well as the operational costs, are strictly related to kms travelled, this is obviously relevant to the optimization of tours by vehicles and, in particular, to the optimization of freight distribution fleets. Previous studies have shown how vehicle routing optimization can determine significant economic savings estimated between 5–30% (Hasle and Kloster [5]) or 5–20% (Toth and Vigo [6]).

On the other hand, local public administrations are developing programs to improve the liveability of cities (Akkad and Bányai [7]; Russo and Comi [4]; Comi and Savchenko [8]; Fraselle et al. [9]). In this context, the question of the urban distribution of goods takes on particular importance. This has led to the development of control policies for freight traffic by placing constraints of a spatial and temporal type (Ranieri et al. [2]).

However, route optimization, as well as scheduling in cities through the exploitation of opportunities offered by the emerging technologies, presents some peculiarities that should foster the development of new methods and models.

This paper aims to analyse the well-known freight delivery problem, i.e., vehicle routing and scheduling problems (VRP), and to discuss innovation guided by the introduction of emerging ICTs (e-ICTs) for optimizing operational costs and reducing traffic impacts. In particular, the learning process of path costs is pointed out as enhanced by such technologies.

The application field of the emerging technologies becomes larger and increasingly more popular every day (Atzori et al. [10]; Tran-Dang and Kim [11]; RTC [12]). It is necessary to define the edges with respect to the studied topics of city logistics. It is also necessary to identify some classes of new technologies that present homogeneity with respect to the investigated topics.

In this way, an investigation of the technologies that mainly refer to the characteristics of vehicles, such as electric propulsion and automation, is out of the scope of this study. However, these technologies are particularly important for increasing safety (e.g., crash sensors) and reducing environmental (e.g., diesel particulate filter) impacts, considering that the vehicle stands alone. Therefore, as detailed in a paper reviewing the scientific and technological literature, the field of investigation is restricted to the technologies that impact directly on city transport (Nikitas et al. [13]; Taniguchi et al. [14]). Furthermore, the areas of interest defined starting from the smart growth (EC [15]), through innovation, and therefore technological platforms and thematic forums, are: energy, transport and information and communication technologies (ICTs). This partnership has the main objective of catalyzing progress in the three intimately connected areas to improve services by reducing energy and resource consumption (EC [16]). Those three areas are urban energy production and use, urban transport and mobility, and urban information and communication technology. It is thus possible to identify four main classes of technologies that impact directly on city logistics towards a smart city logistics: internet of things (*IoT*), blockchain (*BC*), big data (*BD*) and artificial intelligence (*AI*). Besides, considering that such tools are mainly referred to business–to–business, and that retailers usually use different payment methods, *IoT* and *BD* will be mainly investigated.

It is necessary here to recall that, in general, in the *IoT* field, all devices from the installed *IoT* sensors and beacon machines operating in a static position to floating cars in a dynamic context (also considering all vehicles equipped with on-board units that allow information to be sent or received) are included (Croce et al. [17]; Comi et al. [18]).

This paper takes its cue from what is available today for e-ICTs and considers the extensive literature on the subject for the definition and for the solution of the traveling salesman problem (TSP) in all its versions. TSP is considered the base brick for building the different frontiers on fleet management at urban scale. There is a clear lack of a formal unitary treatment of the inclusion of e-ICT in the TSP.

The novelty of this work therefore lies in the unified formulation, within the theory of transport system modelling (TSM), of the TSP problem, with the use of e-ICT for the doubly dynamic learning process of path costs. Therefore, according to such an identified lack in the literature related to a formal unitary treatment of the inclusion of e-ICTs in sustainable urban delivery problems, a unitary formulation of the dynamic process of updating the path costs in relation to the available e-ICTs is proposed. Subsequently, the extensions of the TSP problem to the various cases in the literature are recalled. Moreover, the problems that arise for the company, which has its own *IoT* system, to integrate it with the public one, and the problems of dynamic assignment of time slots, are investigated. The proposed formulation is interesting both for technicians of companies, because it allows them to exploit the opportunities offered by e-ICT available in the city where the companies operate, and for researchers, because it provides the best solution algorithms in relation to the available information to be studied.

Following such an introduction, the remaining part of this paper is organized as follows. Section 2 outlines urban delivery, pointing out the role of emerging technologies in enhancing the learning process of path costs among warehouse and delivery locations. Section 3 investigates the advancement on urban delivery, focusing on two main application fields of e-ICTs, i.e., in-cab communication systems and delivery bay booking. Finally, Section 4 draws conclusions and identifies the road ahead.

## 2. Urban Delivery Problem and Unitary Formulation

In this section, a definition of the problem and the innovation coming from the use of e-ICT are pointed out. Therefore, the advancement in modelling is formalized and its benefit is shown through a real test case.

### *2.1. Problem Definition*

Freight distribution concerns the pick-up and delivery of freight using a fleet of trucks and vans of different dimensions. As a basic rule, vehicles are based on a single depot (warehouse), and the vehicle tours are performed in a single work shift and may include several pick-up and delivery locations. The optimization process of assigning customers (pick-up and delivery locations) to trucks and determining the visiting order of customers and routes refers to vehicle routing and scheduling problems (Taniguchi et al. [19], Ghiani et al. [20]; Russo et al. [21]; Erdogan [22]; Thompson and Zhang [23]). Vehicle routing and scheduling have attracted considerable attention (see, for example, Eksioglu, [24]; Erdoĝan et al. [25]; Dullaerta et al. [26]; Musolino et al. [27]; Kim et al. [28]; Cattaruzza et al. [1]; and references quoted therein), but only recently has the research moved forward to include, in the definition of the problem, information on real-time network status (Sánchez-Díaz et al. [29]; Gomez-Marin et al. [30]; Zhang and Thompson [31]), or even a large amount of information on the previous states of all the arcs/links of the network, both used and not used by the user in his/her past delivery tours. However, at the authors' knowledge, no works integrate the learning process of path/travel costs enhanced by emerging technologies. Thus, the opportunity of further work in this field emerges, both at a theoretical and subsequent operational level. Below, the theoretical level is explored and formalised in order to provide a basis for, and a guide to, the evolution of operational aspects.

The basic information needed for the vehicle routing problem (VRP) are: the location of customers (delivery locations), road network conditions, travel times, and traffic regulations. In addition to this basic information, other specific information for each customer, including the daily request for picking-up/delivering freight, the desired time windows and the assigned driver are given to identify the optimal visiting order and the route for each vehicle.

Travelling salesman problems (TSP) are the basic problems for VRP, which can be described as follows (Lawler et al. [32]; Taniguchi et al. [19]; Erdogan [25]). There are $n$ customers and the cost $C_{ij}$ to travel from customer $i$ to customer $j$ is given. A salesman (vehicle) starts from the depot (warehouse) to visit each customer exactly once and returns to the depot. The problem lies in finding the optimal route (visiting order of customers) that has the minimum total travel cost.

The TSP is solved in the literature using the deterministic or stochastic (Toriello et al. [33]; Archetti et al. [34]) models mentioned above. However, they do not consider explicitly the evolution and perception (i.e., learning process) of travel costs that can be obtained by experimenting with different network configurations. Thus, there is a need to consider explicitly the learning process of path costs germinates. Therefore, this paper deals with the problem of using the e-ICTs within the TSP, which allows for more knowledge on the real past and current evolutions of the network to be acquired.

In fact, e-ICTs can modify various elements of the real system, with the information that derives from them, and this paper deals with the modifications that must be included in the models to simulate the presence of the different e-ICTs in the real system, which modifies the perceived path costs.

Within the framework defined by the TSP, the e-ICTs intervene in the knowledge of the cost of the link which, for this intervention, modifies the nature of going from static to dynamic. The modifications are many in relation to the multiplicity of devices (e.g., minute by minute, hour by hour, day by day) of the various types of e-ICT available on the market. The various e-ICTs are then recalled in aggregate form in relation to the functions in which they intervene. As mentioned, the modifications concern the transformation of the cost from static to dynamic. In the dynamic area, the main changes concern:

- within-day changes that are achieved with the use of *IoT*;
- day-to-day changes that are obtained with the use of *BD*.

### 2.2. The Role of Emerging Technologies

Path costs on time $\tau$ of day $t$, $\boldsymbol{C}$ [$\tau$, $t$], can be expressed as a function of path attributes depending on time $\tau$ of day $t$:

$$C[\tau, t] = \psi(X[\tau, t]), \tag{1}$$

where

- $\boldsymbol{C}[\tau, t]$ is the vector of path costs on time $\tau$ of day $t$, whose elements are the costs of paths from customer $i$ to customer $j$;
- $\boldsymbol{X}[\tau, t]$ is the vector of path cost attributes, whose generic element $X_{hk}$ is the value of attribute $h$ of path $k$ on time $\tau$ of day $t$.

Users can estimate such attributes according to a learning process synthesized in Figure 1. Generally, learning points out both the evolution of $\tau$ and the evolution of $t$ (Cascetta [35]). In addition, for some attributes, the value experienced (tested) in previous periods $\boldsymbol{X}[t-1]$, $\boldsymbol{X}[t-2]$ and, for other attributes, the value updated by the user at each time $\tau$ in day $t$, can be considered through the availability of real-time information.

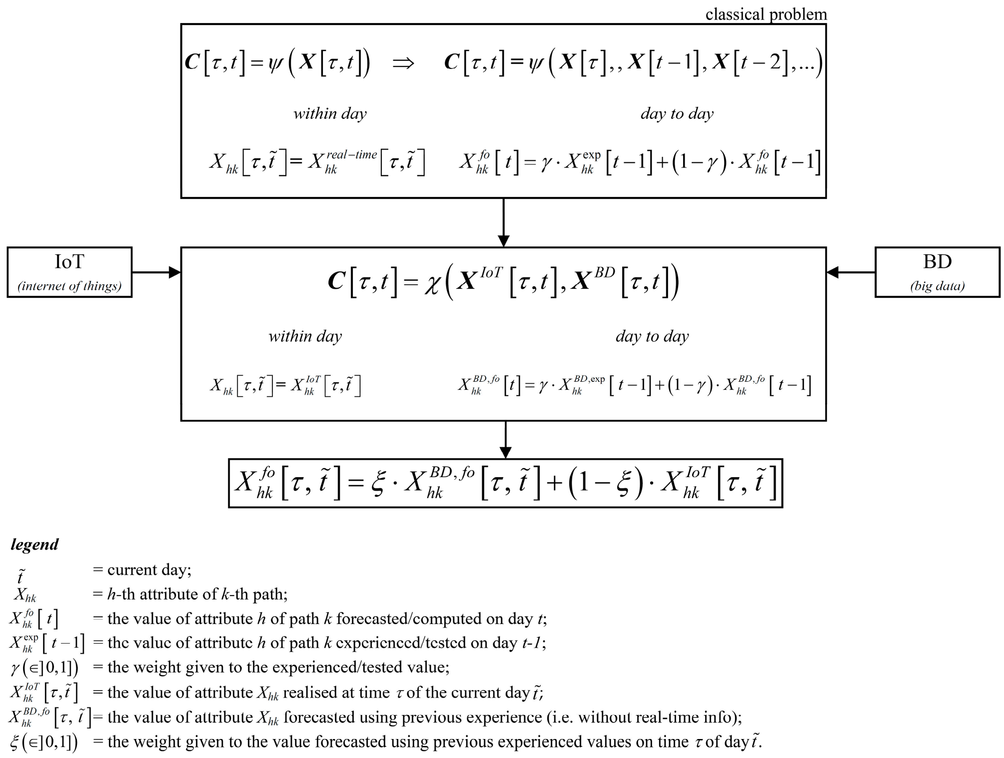


**Figure 1.** Learning process of path attributes enhanced by emerging technologies, *IoT* and *BD*.

Pointing out the role of emerging technologies (i.e., *IoT* for obtaining real-time configuration of the network and *BD* for highlighting the inter-period evolution) in forecasting path attributes, the Equation (1) can be updated as follows:

$$C_{ij}[\tau, t] = \chi\left(X_{ij}^{IoT}[\tau, t], X_{ij}^{BD}[\tau, t]\right), \tag{2}$$

where

- $C_{ij}[\tau, t]$ are the costs of paths for going from customer $i$ to customer $j$ on time $\tau$ of day $t$;
- $X_{ij}^{IoT}[\tau, t]$ are path cost attributes of all paths for going from customer $i$ to customer $j$ on time $\tau$ of day $t$, computed through *IoT*;
- $X_{ij}^{BD}[\tau, t]$ are path cost attributes of all paths for going from customer $i$ to customer $j$ on time $\tau$ of day $t$, computed using past data available thanks to *BD*.

Therefore, as shown in Figure 1, the emerging technologies modify the considered approach, both for daily dynamic and weekly planning. In the planning (day-to-day dynamic), there is the possibility to use *big data* in the off-line analytics and decision making in regards to the main variables to be forecasted in a given temporal period. In the daily activity of management and control (within-day dynamic), the use of *IoT* becomes crucial to update the model with real-time information.

Merging past (*BD*) and real-time information (*IoT*), the value of attribute $X_{hk}$ at time $\tau$ of the current day $\widetilde{t}$ can be determined as follows (Figure 1):

$$X_{hk}^{fo}\left[\tau,\ \widetilde{t}\right] = \xi \cdot X_{hk}^{BD,fo}\left[\tau,\ \widetilde{t}\right] + (1-\xi) \cdot X_{hk}^{IoT}\left[\tau,\ \widetilde{t}\right], \tag{3}$$

where

- $X_{hk}^{fo}\left[\tau,\ \widetilde{t}\right]$ is the value of attribute $X_{hk}$forecasted at time $\tau$ of the current day $\widetilde{t}$;
- $X_{hk}^{IoT}\left[\tau, \widetilde{t}\right]$ is the value of attribute $X_{hk}$ realised at $\tau$ of the current day $\widetilde{t}$; such information is available by means of the *IoT* that reveals the current evolution of the network performance; for example, the travel time ($X_{hk}$) that vehicles are experimenting at day $\widetilde{t}$ in travelling at $\tau$ on the same path $k$ used in the past days; note that such information is actualised for each time $\tau$ in the whole network;
- $X_{hk}^{BD,fo}\left[\tau,\ \widetilde{t}\right]$ is the value of attribute $X_{hk}$forecasted using past experienced values and thus without real-time information; it is given by *BD* at time $\tau$ of day $\widetilde{t}$;
- $\xi$ ($\in$] 0, 1]) is the weight given to the value forecasted using past experienced values and thus without real-time information, given by *BD* at time $\tau$ of day $\widetilde{t}$; such a value of $\xi$ is considered fixed, but in a more general way it can be considered variable with $\tau$, and close/equal to *0* for the link where the vehicle is moving.

Subsequently, the TSP can be formulated, using Equation (2) for the costs, as follows:

$$\text{minimise } Z\left[\tau, \widetilde{t}\right] = \sum_{i=1}^{n}\sum_{j=1}^{n} C'_{ij}\left[\tau, \widetilde{t}\right] \cdot x_{ij}, \tag{4}$$

Subject to

$$\sum_{j=1}^{n} x_{ij} = 1 \forall i \in N \tag{5a}$$

which constrains to have only a single route from customer $i$ to the other customers;

$$\sum_{i=1}^{n} x_{ij} = 1 \forall j \in N, \tag{5b}$$

which constrains to have only a single route to customer $j$;

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in N; \tag{5c}$$

$$\sum_{i \in Q} \sum_{j \in N \setminus Q} x_{ij} \geq 1 \quad \forall Q \subset N(Q \neq 0, Q \neq N), \tag{5d}$$

which indicates that the route should visit each customer exactly once and continuously (i.e., no sub-tours are allowed);
where:

- $C'_{ij}[\tau, \tilde{t}]$ is the cost of path from customer $i$ to customer $j$ on time $\tau$ of day $\tilde{t}$;
- $N$ is the set of $n$ customer to serve;
- $x_{ij}$ is the decision binary variable.

It is important to note that the formulation proposed here allows us to model both the presence of information arriving in real time and the enormous mass of information deriving from what happened previously in the network (i.e., the days before or/and the hours before). The problem formulated has different variants. In its basic version, it has been shown to be NP hard.

### 2.3. Case Study

The proposed planning framework has been applied to a case study in Rome (Figure 2). It has been assumed that an operator has to serve 10 customers during a working day. For avoiding overlapping effects, the attention is paid on customer sequence and only travel time is considered as a path attribute ($X$ = path travel time).

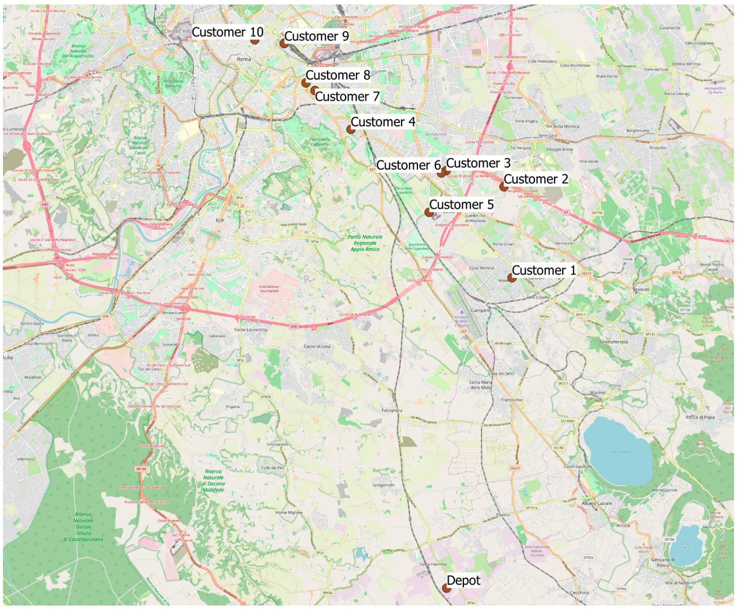


**Figure 2.** Study area (based on OpenStreetMap).

Delivery starts from *Depot* at 9:30, and each customer has a specific service time as reported in Table 1. Using API from Bing and VRP_Spreadsheet_Solver (Erdogan [22]), the travel time on the real road network has been collected for several working days. Using the *average* travel times, the best customer sequence has been calculated (Table 2). Referring to a day $\tilde{t}$ (e.g., Monday) at time 9:30, the best tour has been calculated and compared with that coming from the average revealed-path travel time and a real-time one. As reported in Table 2, the best tour calculated through Equation (4) is different than that calculated with the average value. Both in Tables 2 and 3, the first row is the baseline result computed using average values, while the rows below report the results computed using the proposed method. Subsequently, after serving customer 2 (indeed, with average daily travel times, the best sequence suggests a visit to customer 4), at 10:15 using the real-time travel time, the tool suggests visiting customer 1. The suggestions (updated at the end of the current customer visit) from the tool continue until all customers are served. In order to mitigate the random daily effects, as suggested by Equation (3), the real-time information should be merged with that coming from the previous day (*average* in Table 3; $\xi = 0.70$). It emerges that the sequence of customers visits differs compared to the average, and it uses only real-time data (Table 2). After, a further research challenge emerges, i.e., to define the best weight to give to past (*BD*) and current (*IoT*) values. In fact, using only the past information as shown in Table 2, extra costs that derive from the real-time status of the network can be quite different, e.g., compare *average* and 9:30 optimal tours in Table 2. On the other hand, specific disruptions can condition tour definition, but they can be solved quickly (network returns close to the average status) and the started tour becomes non-optimal. As emerged from the results of Table 2, according to the network performance evolution, after 11:34 the sequence of visits does not change. In particular, it shows that the sequence (3-6-4-7-8-9-10-D) is quite opposite to the average one, where the last customers are visited as the first ones.

**Table 1.** Service time at customer (hh:mm).

| Customer | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* |
| 0:10 | 0:21 | 0:14 | 0:24 | 0:11 | 0:14 | 0:19 | 0:15 | 0:22 | 0:10 |

**Table 2.** Sequence of customer visits through real-time travel time.

| Departure Time | Order of Customer Visits | | | | | | | | | | | Driving Time [hh:mm:ss] | Working Time [hh:mm:ss] | Δ Driving Time | Δ Working Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***average*** | *D* | *4* | *7* | *8* | *10* | *9* | *2* | *1* | *6* | *3* | *5* | *D* | *02:28:45* | *05:08:45* | | |
| 09:30 | D | 2 | 1 | 6 | 3 | 9 | 10 | 8 | 7 | 4 | 5 | D | 02:19:00 | 04:59:00 | −6.55% | −3.16% |
| 10:15 | 2 | 1 | 3 | 7 | 4 | 6 | 5 | 8 | 9 | 10 | D | | 01:54:00 | 04:34:00 | −23.36% | −11.26% |
| 10:52 | 1 | 5 | 6 | 3 | 4 | 7 | 8 | 9 | 10 | D | | | 01:51:00 | 04:27:00 | −25.38% | −13.52% |
| 11:16 | 5 | 3 | 6 | 4 | 7 | 8 | 10 | 9 | D | | | | 01:55:00 | 04:32:00 | −22.69% | −11.90% |
| 11:34 | 3 | 6 | 4 | 7 | 8 | 9 | 10 | D | | | | | 02:05:00 | 04:45:00 | −15.97% | −7.69% |
| 11:49 | 6 | 4 | 8 | 9 | 10 | D | | | | | | | 01:57:00 | 04:37:00 | −21.34% | −10.28% |
| … | | | | | | | | | | | | | | | | |

Δ = variation with respect to the *average* sequence of customer visit. *D* = depot.

**Table 3.** Sequence of customer visits through average and real-time travel time merging ($\xi = 0.70$).

| Departure Time | Order of Customer Visits | | | | | | | | | | | Driving Time [hh:mm:ss] | Working Time [hh:mm:ss] | Δ Driving Time | Δ working Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***average*** | *D* | *4* | *7* | *8* | *10* | *9* | *2* | *1* | *6* | *3* | *5* | *D* | *02:28:45* | *05:08:45* | | |
| 09:30 | D | 2 | 1 | 6 | 3 | 5 | 4 | 7 | 9 | 10 | 8 | D | 02:34:00 | 05:14:00 | 3.53% | 1.70% |
| 10:15 | 2 | 3 | 1 | 7 | 4 | 6 | 5 | 8 | 9 | 10 | D | | 02:04:08 | 04:44:08 | −16.55% | −7.97% |
| 10:53 | 3 | 6 | 1 | 5 | 4 | 7 | 8 | 9 | 10 | D | | | 01:55:01 | 04:35:01 | −22.68% | −10.93% |
| 11:17 | 6 | 1 | 5 | 4 | 7 | 8 | 9 | 10 | D | | | | 02:17:51 | 04:57:51 | −7.33% | −3.53% |
| 11:38 | 1 | 4 | 5 | 7 | 8 | 9 | 10 | D | | | | | 02:01:17 | 04:41:17 | −18.47% | −8.90% |
| 12:03 | 4 | 5 | 7 | 8 | 9 | 10 | D | | | | | | 02:04:53 | 04:44:53 | −16.05% | −7.73% |
| … | | | | | | | | | | | | | | | | |

Δ = variation with respect to the average sequence of customer visit. *D* = depot.

Referring to driving and working time, which is one of the main headings of costs supported by transport and logistics operators (*economic* sustainability), the suggested method allows a significant travel time reduction, estimated in the case study of more than 20% compared to using average travel times. Proposing shorter paths according to the real-time configuration of the network, trucks drive on low congested roads, with significant benefits in terms of pollutant emissions (*environmental* sustainability) and interferences with other road users (*social* sustainability). As shown in other studies, travelling on less congested roads can push an increase of average travel speed with lower emissions of pollutants (Munuzuri et al. [36]; Hammani [37]). Furthermore, if the driver chooses the shortest route only in terms of travelled distance, then he might reach his destination faster if no congestion occurs. Due to the fact that he usually moves in highly congested daily-time periods (e.g., 8–10 a.m.; Nuzzolo et al. [38]; Comi et al. [39]), there may be a significant increase in delivery costs. Thus, considering that travel delay within inner-city areas can be also due to the significant pedestrian flows (e.g., crossing the lanes), avoiding congested roads may help to reach significant outcomes in terms of traffic safety. In fact, trucks tend to produce serious consequences when involved in collisions with passenger cars or pedestrians (Lemp et al. [40])

## 3. Advancement for Urban Delivery

According to the opportunity offered by e-ICT for improving the sustainability of urban delivery, we focus below on the advancement deriving from its introduction: benefits of e-ICTs for the different variants of VRP, the opportunity offered to merge information coming from private and public *IoT*, and innovation in introducing booking delivery bays.

### *3.1. From TSP to Advanced VRP*

Starting from the presented formulation for TSP with the dynamic updating of path costs by means of Equation (3) (i.e., learning process of path/travel costs), the main variants are descriptively (given that it is out of the main scope of this paper) recalled, turning to the literature for the formulation of specific constraints that must be added to the equations before being introduced (Daganzo [41]; Ghiani et al. [42]; Farahani et al. [43]):

- the symmetric travelling salesman problem, where each edge (road link) has the same cost in the two directions;
- the node routing problem, with capacity and length constraints (DC-VRP); considering a capacity dimension for the vehicle and a maximum operating time (e.g., electric vehicles);
- the node routing and scheduling problem, with time windows (VRP-TW), which happens when one or more customers need to be served in specific temporal windows;
- the edge routing problems, commonly known as the Chinese postman problem, where it is necessary to travel along all edges and all nodes of a defined list;
- the multiple vehicles for routing problem, where the Equations (5a) and (5b) can be updated to include the number of identical vehicles at disposal;
- the vehicle routing problem, with reverse for backhaul (VRP-B), when some customers are required to pick-up parcels to backhaul to the depot;
- the vehicle routing problem with pick-up and delivery (VRP-PD), as in the previous one, but each customer can ask for delivery and pick-ups in the same time.

Other variants of VRP exist with similar basic formulation and heuristic solutions (Ghiani et al. [42]; Farahani et al. [43]; Kim et al. [44]).

### *3.2. In-Cab Communication Systems: IoT by Private and Public Entities*

The in-cab communication systems allow the driver to communicate with their company planners, as well as with customers by voice or computer to update the VRP. They use the same formulation of the basic VRP, but with some updates given by the *IoT* systems of the enterprise. Note that, in the formulation of Section 2, the *IoTs* are those present in the network and owned by the public administration.

This system integrates the capabilities of recent mobile telecommunication and the *IoT* (e.g., sensory and data measurement systems) on the vehicle into a unified framework, and has the feature of maintaining a permanent communication among the data acquisition (i.e., *IoT* available by public administration and enterprise) and control modules allocated on the vehicles of the enterprises. It can also supervise and control the transportation processes, assist the driver in decision making, and support the coordination of transport activities. It also provides an information database for all participants for supporting exchanges in value, as well as of specific user characteristics/features (i.e., *blockchain*). For example, information on the retailer availability in receiving freight can be communicated.

The *IoT* of the public administration integrated with the *IoT* of the enterprise allows decisions to be made using *AI*, as well. Thus, Equation (2) can be updated considering the two types of *IoTs*.

Subsequently, the system provides the possibility to restart the calculation of Equation (4) in order to meet the best new solution, considering the introduction or the elimination of a customer from the set of $n$ customers previously defined.

The type of systems considered in this paper points out the possibility to introduce exogenous information (e.g., vehicle sensors and data measurement systems) given by private entities in the tool (models and algorithms) defined in Section 2.

Furthermore, urban delivery and *IoT* can benefit through the innovation in connectivity. Over the past decade, both short- and long-range vehicle communication technologies have been developed and introduced in the transport domain with the primary goal of improving traffic safety and efficiency. At this moment, commercial vehicles equipped with this ITS-G5 technology have recently become available ([12]). Moreover, at several locations in Europe, this technology has also been deployed for infrastructure. In regards to long-range communication, vehicle-to-network (V2N) occurs between vehicles and cloud back-end servers via regular 4G (LTE) and 5G mobile network. 5G promises much more bandwidth, lower latency and the possibility to connect numerous devices, compared to LTE. Currently, a lot of research is being performed to find out how exactly these potential benefits can be achieved [12].

### *3.3. Slot Booking Systems: Dynamic Time Windows and Diachronic Network*

Slot booking systems are usually used to co-ordinate and plan freight vehicle arrivals at major sites generating large flows, as well as for booking space for delivery operations. In this way, it can be considered as another extension of VRP.

The usual initiatives in this group attempt to ensure that vehicles have suitable places to park to perform their activities. Proper allocation of space for parking and loading/unloading freight—both on-street and off-street—is important, because in many city centres and business districts, parking is very limited, which translates into freight vehicles double-parking or spending considerable time circling a block waiting for a parking space, as well as trucks extending into sidewalks and roadways while docking in undersized loading areas.

The main functions necessary for a slot booking system integrated in the VRP one should be, for example, assuming to deliver within a limited traffic area (LTZ):

- information about the availability to access in the LTZ,
- information about the status of delivery bay occupancy within the LTZ,
- possibility to book delivery bay or access slice in advance,
- control the right access, occupancy and use of parking areas.

The problem of time slots arises today in a dynamic form, as public administrations have often defined time windows for the use of both reserved lanes and reserved parking spaces. Both such uses have dynamic allocation. In relation to this, it is particularly important that the single vehicle of a fleet can adapt to the possibilities that may arise during the day, such as the dynamic availability of slots in the lanes or in the parking spaces (Roca-Riu et al. [45], Comi et al. [46]).

Although the main feature of the systems consists of the delivery tour, the main tools implement a travelling salesman problem (TSP) for identifying the optimal routes to serve multiple customers. However, the choice of these optimal paths is constrained by users' constraints, such as the time windows in which to make deliveries and the requirements related to the type of goods. Other binding factors are the availability of parking areas to be used for loading and unloading, and their distance from the delivery locations to serve.

Usually, a solution for a definition tour problem could also be found starting from a pre-defined sequence of deliveries and/or from a set of constraints related to time windows when deliveries need to be performed. In these cases, travelling salesman problem (TSP) models could be used and usually heuristics approaches are chosen on large instances, due to the implicit TSP model complexity. On the contrary, the tool presented by Comi et al. [46]) approaches both the problem of choosing the best timing of the deliveries—also choosing the on-street delivery bay to be used for each destination, if more than one is available—and at the same time aims at reducing the tour time as much as possible.

A further possibility is to use the given formulation, but while implementing the algorithm using a diachronic network (Nuzzolo et al., [47]; Rambha et al. [48]; Nuzzolo and Comi [49]; Eltved et al. [50]), where the temporal windows are defined in each spatial node referring to a day and inserting two temporal nodes for each window.

In the approach, as generalised TSP, the *IoT* can be used in daily decision making to improve the within-day knowledge, whereas the *big data* can be used to update the weekly decision making by means of *AI* models. Different possibilities are given by the use of VRP variants coming from the specification of Equation (4). In every case, if the specific commercial aspects with transitions of value are considered, the *blockchain* element can be introduced.

## 4. Conclusions

The developed work allows some conclusions to be reached, starting from the consideration that the TSP problem is a particularly important problem in the field of city logistics, as well as that learning process of path costs, as enhanced by emerging technologies, needs to be considered. A case study was also reported to point out the opportunity and benefits coming from including such a learning process in the current TSP problem.

The urban freight distribution industry is moving towards control solutions by public administrations (Comi et al. [51], De Marco et al. [52]). Thus, the relationship between fleet managers and public administrations is becoming increasingly complex. In fact, on one hand, the creation of restrictions given by the administrations for freight vehicles determines to which specific space and time slots are assigned; on the other hand, the availability of information on the state of the network by public information gives an important potential advantage.

The public administration must pursue sustainability objectives that require ever-greater control over the different traffic components. At the same time, local administrations are always equipping urban areas with integrated devices capable of participating in an *IoT* network. Therefore, they have the availability to record what happens daily in the network, thus creating *big data* also available for companies. The approach proposed here allows fleet managers to use models that consider the information offered by public administrations, thus transforming the potential advantage into a real advantage.

The proposed approach is increasingly important because it tends to create a smart city (Russo et al. [53,54]), where the three basic elements (ICT, transport, and energy savings) are integrated. Further research developments must address the calibration of the parameters and the advancement of the specification proposed in relation to the different slot management policies implemented by the public administration.

The work is important for the technicians of the companies who can combine information that has different origins, obtaining the best results for freight delivery. The work is useful both for e-ICT researchers, because it allows one to identify how and where e-ICTs are used in the transportation field, and for transport researchers, because it allows them to define the field of use of the different e-ICTs, and then to proceed in the modelling.

Therefore, as discussed throughout this paper, the strength of the proposed methods mainly consists in the benefits in optimizing costs, not only for operators, but also for collectivity, in general. Besides, the e-ICTs open new opportunity to such a logistics sector; for example, as done by Walmart for food delivering, smart devices (*IoT*) can be securely tied to, or embedded in, the physical product to autonomously record and transmit data about item condition, including temperature variation, to ensure product integrity, as well as any evidence of product damage (*BC*). Of course, collecting data (*big data*) on the transport network and on the service provided allow operators to identify eventually critical stages in their services with classical methods or through advanced machine learning techniques and to optimize their services (*AI*). Such an innovation suffers the penetration and acceptance by the operators, which are jealous of their business and related data. Therefore, the future urban challenges towards a more efficient policymaking on urban freight logistics requires cities to enhance their data collection capabilities, while private logistics and/or e-commerce (like food delivery) companies (Campisi et al. [55], and Russo and Comi [56]) and services should be encouraged to share data, considering what are the most useful data, how companies can be encouraged to share and systematize data. If these data were collected, contextualized, and combined more optimally, this would enhance machine learning (*AI*) models' ability to infer useful patterns from both historical and real-time data. Understanding barriers and opportunities as well as developing local capacity related to data sharing within the urban and peri-urban transport system could be a first step to encourage private and public organizations to share their transport data. Subsequently, this benefit could push new applications and support the optimization of urban freight mobility as required by the international trends (e.g., Agenda 2030, Sustainable Development Goal 11, as well as by sustainable urban mobility plan—SUMP and sustainable logistics plan SULP).

Finally, it should be note that this paper is fully a part of the evolution of the smart city, because it directly formalizes the relationship between transport and e-ICTs in order to improve freight distribution, setting as an objective, for example, using electric vehicles. Subsequently, its evolution pushes towards a further-advanced level that provides: the opportunity to design a multilevel delivery path (tour) with nodes (points) where walking for reaching the final customers (e.g., retailers or end consumers' homes, i.e., courier problem) is introduced, the users' choice behavior (i.e., choice updating model) and the issues related to the double dynamic assignment process.

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