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The Role of Optimization and Machine Learning in e-Commerce Logistics in 2030

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Abstract—Global e-commerce sales have reached unprecedented levels in the past few years. As this trend is only predicted to go up as we continue into the '20s, new challenges will be faced by companies when planning and controlling e-commerce logistics. In this paper, we survey the related literature on *Optimization* and *Machine Learning* as well as on combined methodologies. We also identify the distinctive features of next-generation planning algorithms - namely scalability, model-and-run features and learning capabilities - that will be fundamental to cope with the scale and complexity of logistics in the next decade.

Keywords—e-Commerce, Logistics, Machine Learning, Optimization.

I. Introduction

By the end of 2020, global e-commerce sales are expected to reach \$536 billions with a 21.2% annual increase [1]. From a logistics point of view, the challenge is to satisfy customers having higher and higher expectations in terms of timely and cheap deliveries of a increasingly large variety of products. As a consequence, planning and controlling e-commerce logistics will be more and more complex. Companies are dealing with this complexity in number of ways: e.g., they are moving from the classical home delivery service (where a person brings the goods to the customer and hands them over face to face, *Face-To-Face home and office delivery* (F2F)) to some sort of *Non-face-To-Face home delivery services* (N2F) which include deliveries to dedicated shops close to customers, which have agreed to accept such deliveries, drop box deliveries or car trunk deliveries [34].

Despite these organizational measures, e-commerce logistics remain very complex. Here is where *Optimization* and *Machine Learning* come into play. In this article, we review the literature and identify a number of issues that will be key in order to deploy effective and self-learning decision support algorithms to cope with the ever-increasing e-commerce demand in the next decade. In particular, we are focusing on last-mile logistics, defined as the final step of the delivery process from a distribution center to the end-user.

II. Technology Advancements Impacting Logistics

In this section we are reviewing shortly a number of major technological advancements that will have a profound impact on logistics operations:

- the Internet of Things (*IoT*);
- autonomous vehicles, including ground and air drones;
- big data;
- crowd logistics.

A. Internet of Things

According to the IoT paradigm, first proposed in [2] and later developed in [30], in the future everyday objects will have a digital identity and be connected to the internet. They will be able not only to send and receive data but also to make some decisions on the their own (*smart objects*). For example, fridges will be able to monitor the inventory levels of the groceries, through a careful fusion of RFID and vision data, and possibly place replenishment order autonomously. The IoT will make feasible the implementation of the *vendor-based resupply* (or *vendor-based inventory*, *VMI*) paradigm in which the supplier will be in charge of re-supplying the customers.

B. Ground and Air Drones

Another innovation that is expected to have a tremendous impact on deliveries in last-mile logistics is represented by the so-called *autonomous vehicles*, which can be classified as *ground drones* and *air drones*. The former can be further subdivided into autonomous cars or vans, which can make use of traditional roads, and the so-called *slow-moving sidewalk based mini-drones*, which can make use of sidewalks and public transportation vehicles, just like a normal citizen. Of course, the possibility of practically employing autonomous vehicles for deliveries requires to fix a number of issues related, for instance, to security, noise, or to the necessity of vehicles to interact with the consumers. Nevertheless, recent studies agree that *air drones* will be utilized for deliveries in rural areas (together with traditional vehicles), whereas *ground drones* will be in charge of urban distribution [26].

C. Big Data Analytics

Logistics is ideally suited to benefit from the technological and methodological advancements of Big Data Analytics. Nowadays logistics systems manage a massive flow of goods which, in turn, generate millions of transactions every day. Big Data Analytics allow to fully exploit the value of these stream of data in order to optimize resources and improve customer experience. As far as last-mile deliveries are concerned [38], data include those generated by RFID tags attached to delivery items, the location data of recipients, data created by sensors attached to delivery vehicles, data from order management and shipment tracking as well as the position and status of

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delivery crowd members. These big data are used to dispatch requests in real-time as well as to schedule delivery staff and vehicles (or crowd-based pick up/delivery). They may also be used to provide real-time predictions of estimated times of arrival (ETAs) at customers' locations. To this purpose the main methodologies are *Combinatorial Optimization* and *Machine Learning*.

D. Crowd logistics

From a business model point of view, it is very likely that *crowd logistics* will become more and more popular, in the fashion of Uber in the local transportation sector. An automated platform will be devoted to matching the freight transportation demand with the availability of students or part-time workers, who are willing to work as riders. On the same platform it will be possible to follow the freight step-by-step, from the pick-up to its delivery.

III. Optimization and Machine Learning in Logistics Planning and Control: State of the Art

Planning last-mile logistics activities in the e-commerce sector requires dispatching orders to vehicles, scheduling deliveries, as well as defining the routes of the vehicles. Such decisions are strictly intertwined and define a combinatorial optimization problem, which in the scientific literature is concisely referred to as *Vehicle Routing Problem* (VRP). The VRP was defined for the first time in [14]. In its original formulation, a homogeneous fleet of vehicles (located at a central depot at the beginning of the planning horizon) must service a set of customers, with each of them having a demand of a particular product that must be satisfied. Typically, servicing a customer requires an additional service time, which must be taken into account when defining the routes. Moreover, to measure the cost of traveling between locations a cost matrix is used, where costs may represent distances or travel times. In a common problem variant, each customer has an associated time window during which he/she must be serviced. Other formulations consider a heterogeneous fleet of vehicles.

In the classical VRP described above, all its data (e.g., travel times or customer requests) do not depend explicitly on time and are known at the beginning of the planning horizon. However, a great part of distribution planning problems in the e-commerce sector presents features that may change during the planning horizon, and are known in the literature as *Dynamic Vehicle Routing Problems* (DVRP).

In the following, we review the relevant literature concerning optimization algorithms, machine-learning methods, or a combination of both of them, used to solve the VRP and its variants.

A. Optimization

The classical VRP has been widely studied during the last few decades. For books and comprehensive reviews, we mention [42], [20], [27], [9]. Optimization algorithms used to solve the VRP comprise exact and heuristic approaches. Among the former, we highlight the use of *branch-and-bound* [22], *branch-and-cut* [5], and *branch-and-cut-and-price* methods [23], in addition to *dynamic programming* [11] and various *vehicle flow* [28], *commodity flow* [7], and *set partioning* [8] -based formulations.

Regarding heuristic algorithms, solution methods range from the *savings* algorithm [12], *set-partitioning* [35], *cluster-first, route-second* [4], and improving [41] heuristics, to the so-called metaheuristics, like *tabu search* [10], *simulated annealing* [45], and *variable neighborhood search* [46].

In the DVRP case, as customer requests arrive in real time, it is not possible to define a solution a the beginning of the planning horizon. Rather, it must be defined a *policy* that specifies which action to undertake as a new event arises and the system is in a given state. Because of the necessity to obtain good-quality solutions within a very limited amount of time, the focus of the scientific community has been mainly on heuristics and metaheuristics, as tabu search algorithm, both in its traditional and parallel versions ([3], [15]), or local search procedures [36]. In addition to such "traditional" approaches, there is the research stream based on modeling problems as *Markov Decision Processes* (MDP), on the use of *Dynamic Programming* (DP), as well as the development of *anticipatory algorithms*. Examples of these approaches are reported in [19], [40], [18], [44].

B. Machine Learning

The dramatic advances in information and communication technologies observed int the past few decades has provided new possibilities and opportunities for vehicle routing research and applications. Nevertheless, the huge amount of available data has pushed up the use of machine learning methods to develop dynamic routing algorithms.

In particular, a methodology that is widely used for solving vehicle routing applications is *Neuro-Dynamic Programming* (NDP), often referred to as *reinforcement learning*, which is the term used in the Artificial Intelligence literature. To overcome the limits of DP due to the huge size of the underlying state space (the so-called "curse of dimensionality"), NDP uses neural network and other approximation architectures. The methodology allows systems to learn about their behavior through simulation, and to improve their performance through iterative reinforcement. Within this framework, we mention the papers [37], [43], [32], [24], and [31].

C. Combined Optimization and Machine Learning

Another alternative that the research community has started exploring is also the possibility of integrating optimization and machine learning tools and techniques. One of the first contributions in this direction is reported in [33], in which the authors integrate optimization and machine learning to obtain a computer-aided algorithm design in the domain of vehicle routing. Other contributions are reported in [13], [29], [21], and [47].

IV. Optimization and Machine Learning in Logistics Planning and Control: A Vision for 2030

By 2030, efficient e-commerce logistics planning & control algorithms will be in higher demand more than ever before. We have identified their main distinctive features.

A. Scalability

The huge size of the problems will challenge the classical notion of efficient algorithms. Algorithms that used to be considered efficient, according to polynomial-time characterization, will no more be adequate. The algorithms will need to be scalable. It is not just desirable, but essential, that efficient algorithms should be scalable. Scalability is the property of a system to handle a growing amount of work by adding resources to the system [6]. In other words, the complexity of the algorithms should be nearly linear or sub-linear with respect to the problem size. Thus, scalability, not just polynomial-time computability, will be key. Scalability can be achieved by parallelism, advanced sampling and sparsification, among other things. See [39] for a general discussion of these issues.

B. Model-and-Run Features

Last-mile logistics amounts to dispatch requests in real-time as well as to schedule delivery staff and vehicles. Since even moderate-sized instances can be barely solved consistely by available exact algorithm, one must use heuristics. Most ”good” heuristics embedd some sort of neighborhood search into a metaheurisitc framework [16]. Neighborhood search algorithms move from solution to solution in the search space by applying local changes, until a solution deemed optimal is found or a time bound is elapsed. Hence, the design of a heuristic comprises a number of steps, including the definition of a “good” neighborhood structure on the solution space as well as the “tuning” of the parameters characterizing the higher level search strategy. In order to make the metaheuristic efficient, both the local and the global improvement mechanisms need to be tailored *not only* to the specific problem *but also* to: (a) the peculiar distribution of the instances to be solved (*reference instance population*); (b) the imposed time limit; (c) the hardware at hand. Nowadays, this is done by human experts through a time-consuming process comprising problem analysis, literature scouting and experimentation. This means that, if new constraints are added or some constraints are changed, the algorithms need to be re-designed, re-implemented and re-tuned. Since we live in a constanlty changing world, future planning algorithms will need some mechanisms that may derive automatically, without any human intervention, “good” metaheuristics from a description of the planning problem to be solved (e.g., from a given Mixed Integer Programming (MIP) model). The ultimate goal will be to automatically generate metaheuristics that may provide results comparable to (or even better than) those produced by tailored algorithms entirely designed by humans (*human competitive* results; see, [25] for a definition of this notion).

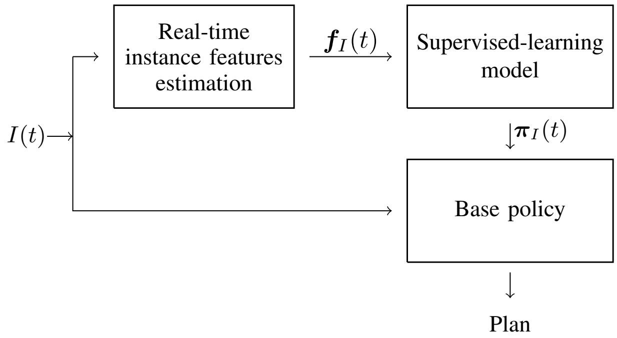

Fig. 1 Steps of the approach

C. Learning Capabilities

Current metaheuristics are characterized by a number of parameters whose values are optimized w.r.t. to a given instance population in a preliminary tuning phase. We envision a new class of algorithms that will be able to recognize the kind of instance to be solved (in particular, its demand pattern, its traffic congestion, ...). In a preliminary stage (*off-line*) the most likely scenarios will be simulated and, for each scenario, a number of policies will be tested. The results will give rise to a dataset that will be used to train a supervised model. At real time (*on-line*), given an instance $I(t)$, its features $f_I(t)$ will be extracted and inputted into the supervised model in order to estimate the best parameter $\pi_I(t)$ setting for $I(t)$. See Figure 1. A preliminary evaluation of this idea can be found in [17].

V. Conclusions

In this paper, we have moved from the continuously increasing trend of global e-commerce sales in order to identify the new challenges that will be faced by companies when planning and controlling e-commerce logistics in the next decade. In particular, we have first surveyed the related literature on optimization and machine learning as well as on combined methodologies. Then, we have identified the distinctive features of next-generation planning algorithms that, in our opinion, will be fundamental to cope with the scale and complexity of logistics towards year 2030.

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