Production and Operations Management

# Master's Thesis

## in Technology and Innovation Management

# Route Optimization
# for take-out deliveries

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In this work, any terms highlighted in **bold** are considered as key points that concentrate a big part of the paragraph's meaning, while those in *underlined italics* are considered to predispose to specialized terms and nomenclature expressions of the field. The simple *italics* are used for emphasizing common terms of reference.

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## Foreword – Acknowledgments

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## Abstract

The restaurant industry has long embraced technology, relying on POS and restocking platforms (i.e. virtual places which do not trade products but rather facilitate transactions between the supply market ends*) to leverage Web 2.0 apps and what comes along with it, like social media reviews (Yelp, Instagram) and ratings (TripAdvisor, e-food etc.).

Now, once again, the food industry begins to capitalize on the rise of the Gig Economy (also called *O2O*, *Sharing* or *On-Demand economy*) and its reshaping forms, as every country is gradually evolving, adopting this new technologically-imposed culture. Millennials increasingly search for flexible, part-time work and, according to the National Restaurant Association, the restaurants industry (which is a big part of the App's target market) has a notably higher percentage of part-time workers than the broader workforce.

This study reviews the existing literature and examines methods that sustain the optimization frameworks (usually referred to as platforms) that control the association between deliverers, goods and store owners in order to study ways to increase fairness and improve the working conditions of deliverers. Thus, as the title of the study suggests, the idea is to keep the **Route Optimization Techniques** per case, study the advantages and disadvantages that they bring to the table and advise for ways that a **meritocratic but equal exploitation** (fairness) **of the emerging opportunities** (here orders) can be beneficial (or marginally beneficial) to all actors, and especially the **deliverers**. For example, a deliverer nowadays works for a specific store (or branded fleet) sometimes distributing a specific set of goods, thus being restricted to work fixed hours at limited areas, receiving a limited salary. During the peak-hours the consumers anticipate the same quality of service which translates into stress for both the shop owners and the deliverers, especially now that the user-rating concept has been so immersive around transactions and more specifically, in this case, to the entirety of the food distribution process.

The proposition is rhetorically constructed to complementarily contribute to the solutions offered in the respective literature, by paying special care to **the democratization of the medium as seen from the deliverer's point of view**, in order to allow for a fair and equal chance for meritocratic access to all available facilities, and thus any potential profit.


* ends here refer to the consumer/customer/requester/client on the **demand** side and the company/firm/producer/ /provider/merchant/restaurant/owner/server on the **supplier** side. These two ends meet through the deliverer/delivery executive/courier/driver/rider/agent/fleet/vehicle of the **mediator workforce** platform (dispatcher/aggregator).

## Structure of Work

The corporate environment of the modern food delivery industry is strongly characterized by the evolution of complex logistic structures, which require tight integration with tools that aim towards quick and tactical decision-making, optimal resource and inventory management, innovative supply chain management and the alignment with the main strategic orientation of the company. The same ideas hold true regardless of the volume and the governance of the entrepreneurial structure in focus, let this be a farmer, a factory, a retail store, an aggregator, or a restaurant.

**Chapter 1** makes a quick overview of the current status of this ecosystem and moves to a brief description of its main issues, the problematic nature of Gig Economies, and the purpose of this work.

Along with the rapid commercial growth of this industry, the academic community has taken over a series of *NP-hard* challenges trying to approach the emerging issues from various operational aspects. Most of the realistic models (especially for vehicle routing) tend to be formulated into mathematical equations with solutions that are inapproximable in polynomial time. This further underpins the level of difficulty and how imperative is the need for novel algorithms and methods of high efficacy and new break-through ideas.

**Chapter 2** mentions the main routing problem archetype, its variants with their main characteristics and constraints, some basic branching methods, and their objectives, providing, where needed, an explanatory mathematical formulation.

In the beginning of **Chapter 3,** we gradually transition from the theoretical analysis of the previous chapter to a pragmatic one that revolves around case studies of the industry, by analyzing some of its fundamental supply chains issues, followed by a few examples of *Vehicle Routing Problems* (VRPs). The chapter continues by citing the influence of the end-users (*preference*, *loyalty* and *behavior*) as the key factor that introduces either directly or indirectly the main sources of uncertainty, in the mix. The next paragraph proceeds by presenting the online delivery applications and the ways that the previous ideas are being projected in their creation. The chapter continues by explaining the conditions under which governmental intervention is recommended, it encourages entrepreneurial compliance in all cases, and completes by making a few mentions in the decision support technologies in food supply management.

On this point it is important to note that the current review is inclined towards the end that sheds a brighter light in the analysis of the works that research the meal delivery routing issues from the rider's perspective.

Towards that end, an important improvement regards the broadening of the decision-making philosophy, where the optimization of quality, time, effort and cost, includes, in a holistic view, every stakeholder involved in the process. In that sense, one of the challenges that this industry faces, which includes a price that is being redeemed in one way or in another by all actors involved, is related to the riders' low income, long hours and bad working conditions that they face, in general.

This is why, **Chapter 4,** raises awareness on a number of papers that mention the main *systemic*, *political*, *algorithmic* and *contingency* risk factors that impair or evoke disruption to the welfare of the low-income service workers.

**Chapter 5** is structured to mention works which introduce ideas that can - apart from optimizing performance - *reduce injustice* and *serve humanitarian principles*, through *induced fairness*, joint distribution solutions, *cooperation* for servicing a common goal and enhancement of *corporate responsibility*. The chapter ends with a number of few practical, well established prior art approaches that focus on fairness and examples of measures that weaken the key injustice catalysts.

The thesis is concluded in **Chapter 6**, beginning with a short recap of the review findings, followed by a series of subsequent conclusions. These points can be used as methodical building blocks in future works that aspire to contribute towards the *equitable income fairness* of the food delivery agents.

The contribution of this work includes a series of insights for the *regulation of the emerging opportunism* in corporate order planning, facilitating a proper balance of the pickup and delivery (PD) assignments of food delivery agents *between Egalitarian equality and meritocracy,* i.e. through *Proportional equality*.

# 1. Introduction

During the past few years, the takeout delivery businesses have been transforming into a very big high-tech industry, with a number of services such as Deliveroo, UberEats, Caviar, Zomato, Swiggy, G2 Deals, GrubHub, Delivery Hero (FoodPanda, Foodora, eFood), Wolt, Doordash, OnFleet etc. growing rapidly while adopting disruptive business models that outperform the conventional market standards. This phenomenon has matured to the point where a very large percentage of the current store owners and deliverers have been forced to adopt these models and to engage with the tools and resources of this new reality. It is actually the end-consumers' demand which has been leading the crest of this transformation wave, introducing and sustaining the standards for today's services that offer a wide range of high-quality products (mainly takeaway food) being delivered on our doorstep within half an hour or so.

## 1.1. Brief review of the current status

The main business models of the start-ups exploiting this evolution can be divided into two closely-interacting approaches. Some of these businesses can leverage their existing user base (like Uber and Caviar), and some have been positioned to mainly serve as restaurant *aggregators* (like Seamless, GrubHub, and Deliveroo to some extent). The former businesses add a value proposition by introducing their fleet to the mix. At the same time, the latter prefer to act as a middleman in the delivery process using a non-capital-intensive approach, usually through the development of a web application that is integrated into the virtual network of inter-connectivity between a docking supplier and the spontaneous demand. In both cases, the best offers of such businesses include operational management through their logistic service. As it is apparent, the two main business models revolve around the idea that the main challenge in today's delivery process is that it needs to be **on-demand**, **affordable**, and **convenient** for both the restaurants and the customer.

## 1.2. Raising awareness on the Gig-Economy Issues

However, although there is a lot of focus given on the driving force of this market, i.e. the end-consumer, there is room for improvement when it comes to the focus given to the serving force on the physical layer of the modern delivery process, which is the actual riders, whether they belong to a specific firm as in-house riders or act as members of a wondering (branded) fleet. The later point is effectively important, when considering the impact of the recent developments on the adjusted regulations (in UK for example) related to the worker's **compensation, insurance and payment** [1] as well as appearing as **a puzzling subject** for the academic community [2]. As regards the working labor status quo of the food delivery industry, it falls directly under the frame of Gig Economies as one of its most characteristic examples (i.e. labor markets characterized by the prevalence of **short-term contracts or freelance work** as opposed to permanent jobs) [3]. Consequently, introducing such an application to the food delivery industry comes with a lot of challenges as well as with a lot of benefits for both the existing workers and the employers (shop-owners) which need to be properly handled when considering the actual algorithms that will be called to propose **realistic, high-performing** but also **fair solutions** to this huge logistic challenge. The aforementioned gig-economy issues may raise considerations and skepticism on the employment conditions of the deliverers but, when turned over their head, these are the same ones that can provide some guidance and enlightenment for the next steps to take and what academic path to follow towards the improvement of the existing solutions.

As mentioned, this review focuses on the riders, one of the four main stakeholders of the On-Demand Food Delivery (ODFD) industry. The riders play a key role they interact with all three stakeholders left, the restaurants, the digital (online) platform and the customers (see Figure 1). They ensure safe and timely pickup and delivery of the orders, as they are aware of the road peculiarities and traffic uncertainties. Also, they act as liaisons exercising the restaurant's public relations and communicate the customer's experience back to the restaurant owner to enhance the satisfaction of both ends.

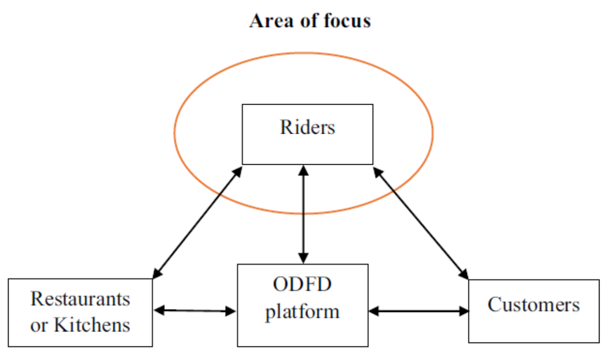



**Figure 1. ODFD actors and relationships [4].**

## 1.3. Problem Statement

The actual logistic challenges clearly fall under the optimizing of vehicle routes, trying to use the available drivers **in a non-monopolistic manner**, while having the delivery orders covered **as quickly as possible**. The orders are expressed in real-time, providing time-windows of less than half an hour, with drivers being already out on the road, ready to collect and deliver to a multitude of locations. There are thousands of papers that have been written over the last decades on the **vehicle routing problem** (VRP) and its variations [5-7] which mainly include methods of generating efficient routes for a set of vehicles starting at a depot and delivering to many scattered customers, under certain constraints and conditions.

The specific problem does not necessarily start at a single depot from which all vehicles begin. Sometimes the goods need to be picked up from various (random) places. So, picking up from one place and delivering to another, while none of them is the depot, is a different kind of a routing challenge, namely **the pickup-delivery problem**. There are many researches on this front too, however the norm is for the orders to arrive long after the drivers have begun their shift, and sometimes there is no notion of a shift at all (depending on the employment contract or the free-lancing activities of a deliverer) so there is no time period available to plan for a big set of routes, like for example during the night. Instead, the planning of the routes has to evolve over the night as the new orders arrive. This upgrades the type of challenge to a **dynamic pickup delivery problem** [8,9].

One possible extra step towards the utilization of all available arrows in our academic quiver, may lead us to **the use of the big data (and metadata)** of existing orders. The modern analytics techniques can then deal with **probability distributions of the potential future orders** to help us in a twofold way:

- firstly, on a preliminary level to formulate **the initial conditions** as a beginning state for the simulations and
- secondly to facilitate on the **re-shaping of the dominating routes** while the algorithm adapts its solution to stochastic changes. This approach suggests that the challenge transforms into a **dynamic and stochastic pickup and delivery problem** [10-12].

As far as it concerns the nomenclature of VRPs, the realistic problem that has been described so far, can be categorized under a few specific main classes. Each one of this classes sets the conceptual (and to some extent the mathematical) formulations, similarly to a generic frame under which certain properties and constraints of such problem categories are most prominent. In that sense, the problem can fall under the **Vehicle Routing Problems with Time Windows** (VRPTW) [13] and more specifically under the **Capacitated Vehicle Routing Problems** (CVRP) [14], meaning that the time-frame of the actual servicing and the capacitance of the vehicles fall under some constraints (i.e. they are practically bounded) and as such need to be considered as dimensions of the problem.

Additionally, the specific problem falls under the **Open Vehicle Routing Problems** (OVRP) [15] since the vehicle does not need to return to the depot after servicing the last customer. Finally, one important characteristic of the specific problem is that the vehicles can (and need to) use multiple depots, making the challenge to fall under the **Multiple Depot Vehicle Routing Problems** (MDVRP) [16-19].

### 1.4. Hypothesis and Proposition based on the review findings

Currently in both the commercial market and in the academic literature, most of the focus is paid towards platforms and algorithms that **optimize certain aspects of the supply chain and logistics** by analyzing the operations related to the order pick-up and delivery process. One good typical resource for such approaches is given in [20] where the insights that can be emerged for the proper design of the actual surrounding network is what dominates the initiative for the whole research. Such work is very important as it can provide valuable suggestions to individual market players (mediators, aggregators, vehicle fleet owners etc.) **to stimulate and/or fine-tune** their products and services.

However, there is one aspect of the whole equilibrium in this neural ecosystem that is usually underestimated or even neglected. This is related with an aspect that suggests that the applied 'artificial intelligence' (which is usually the product that is being integrated in such a network) is effectively nothing but a set of applied solutions that run in an individualistic way, on a virtual board of emerging opportunities, trying to relish the fruits of their optimal decision making. This is most probably done in a **symbiotic** but at the same time **competitive** way, leading to **idiosyncratic** behaviors, as the algorithms run like agents on functions that suggest maximization of individualistic profit rather than operators that **manage resources with fairness and social balance** in mind.

Although the argument to this can be the fact that such forces are usually what drives the free market and to some extent they should be encouraged, the point is that this is true for the level of competitive fleets (although this is also debatable) but it is not necessarily preferable on the level of fleet members.

There are ways to balance such behaviors to maximize common wealth and to satisfy some lower bounds of fairness, like for example the **geographical segmentation** (used by Uber). The hypothesis here however is that in the general case the proposed algorithms and methods in the pickup and delivery market is best **to address such monopolistic issues and to compensate for systemic privileges** which, if not balanced by the algorithm, there will still be equality enforcing policies needed to be applied, outside of that system (like fiscal policies, state regulations or even private actions).

The pragmatic implementation that can promote such ideas is the creation of a mobile (or web) application which will be constantly adjusting its solution according to the preferences and the location of the user that has stated that he/she wished to engage to the platform. This means that anyone who wishes to enter as a deliverer, let this be someone who is actually a member of a certain fleet, an in-house deliverer (of a certain store/shop owner), or a freelancer, will be welcomed as the system is seamlessly allowing for all existing (competitive) structures to continue working, as is.

The offering of the option to engage into this network through this alternative medium is based on the assumption that its value proposition is attractive under certain conditions. These are a) the wish by all stakeholders to enjoy the **balancing of the offer-demand distribution**, b) the facilitation towards the **rightful payment** and **accurate rating** of deliverers and store-owners individually (meaning in a meritocratic way, without biasing the routing selections in an attempt to maximize a global variable) while, at the same time, c) assuring some **high standards for the end-customer's overall food ordering/delivery experience** (by minimizing waiting time and maximizing scope/type of services – which are actually part of the conventional constraints already applied to most basic VRPs).

In practice, such a balancing has been attempted quite a few times during the past 3 years (2019 to 2022), by external enforcement attempts (i.e. outside of the aggregators' automated logistics) coming from the end-customers (which are the powerful drivers of all industries) according to what the latter consider as **socially justifiable**. Some of the cases include:

- lowering the order rate during raining,
- boycotting specific aggregators policies that deteriorated the deliverers working conditions,
- contributing by participating on labor strikes for that matter, and
- ordering outside the peak delivery times during Covid-19.

These were all cases where the masses of people quickly (in a matter of a few weeks) aligned to a **common moral principle**, and rallied into parties holding a **common manifesto** (i.e. a set of rules) **against a systemic injustice**. This demonstrates the flexibility possessed by all social forms in claiming and implementing functions, outside the scope of regulations, and the law-enforcement, if need be, which is a notion that needs to be well established when reviewing the applicability of the mathematical models that attempt to manage the gig-economy markets.

# 2. Types of Vehicle Routing Problems (VRPs)

In the past section, paragraph 1.3, makes a few brief mentions on various VRP types. A generic definition that covers a wide range of such problems is the following [21]:

Given: "A set of *transportation requests* and a *fleet of vehicles*",

the problem is to create a plan which covers the following:

Task: "Determine a set of *vehicle routes* to *perform* all (or some) transportation requests with the given vehicle fleet *at minimum cost*, in particular, decide which *vehicle handles which requests in which sequence* so that all vehicle routes can be *feasibly* executed."

As it is also mentioned in [21], this type of problem (the VRP) relates to requests which are usually concentrated around road network points rather than arcs, where the emerging requests are found along street segments of the road network (*Arc Routing Problem*, or ARP). The optimization techniques that have been fully integrated into the information systems of modern corporations are able to model most of the natural parameters of the VRPs, as these arise in real-world applications.

The journals that publish the academic and industrial works of the international researchers on the variants of the VRP are the ones focusing on "*Operations Research*", "*Heuristics*" and "*Transportation Science*". The community is highly active and very much interested in the practical relevance of these variants. The paragraphs to follow will focus on the most common types (archetypes) and variants of VRPs.

## 2.1. The basic VRP archetype

The capacitated VRP that has been mostly studied in academia along with the *Traveling Salesman Problem* (TSP). In this problem the distribution of the goods begins from a single depot, signified as point $0$ (zero). The goods are to be distributed to a set of $n$ other points, the customers, $N = \{1, 2, \ldots, n\}$. The amount of goods that are delivered to point (customer) $i$, where $i$ belongs to $N$, and is the customer's demand which is signified as $q_i > 0$. This scalar may denote the weight or any other dimensional property of the goods which can accumulate towards a restriction limit that will pose a threat to the proper completion of the delivery process. The vehicles of the fleet, which is considered to be *homogeneous*, are denoted as $K = \{1, 2, \ldots, |K|\}$ and all have a capacity

$Q > 0$ and also operate at equal costs. It is assumed that a vehicle which has to service a subset $S$ of the customers ($S \subseteq N$) begins at depot zero, reaches each one of the customers of $S$ and then returns to depot zero. It is also assumed that a vehicle that moves from point $a$ to point $b$ incurs a travel cost of $c_{ab}$.

This information can be formulated in a graph (directed or undirected). For convenience let the depot demand be defined as $q_0 = 0$. Let $V = \{0\} \cup N$ denote the set of nodes (or vertices) of the problem. For the cases that the cost for travelling between point $a$ and point $b$ is the same, the graph $G = (V, E)$ is stated as complete and undirected and it holds an edge set $E = \{e = \{a,b\} = \{a,b\} : a,b \in V, a \neq b\}$ and edge costs $c_{ab}$ for $\{a,b\} \in E$. When, one or more pairs of the nodes present asymmetric costs such that $c_{ab} \neq c_{ba}$, the graph is stated as a complete digraph $G = (V, A)$ that has an arc set of $A = \{(a,b) \in V \times V : a \neq b\}$ and arc costs $c_{ab}$ for $\{a,b\} \in A$. On this point it is important to note that $|E| = n(n+1)/2$ and $|A| = n(n+1)$, which leads to the graph containing $O(n^2)$ links. In overall, the CVRP graph is described as a weighted graph $G = (V, E, c_{ab}, q_i)$ or similarly a weighted digraph $G = (V, A, c_{ab}, q_i)$ including the fleet size information about $|K|$ and the vehicle capacity $Q$.

A solution of the problem as stated above is given by a *route* (or a tour) which is formulated as a sequence $r = (i_0, i_1, i_2 ..., i_s, i_{s+1})$ where $i_0 = i_{s+1} = 0$ for the visited set of customers $S = \{i_0, ..., i\}_s \subseteq N$. The cost of this route is $c(r) = \sum_{p=0}^{s} \left(c_{i_p, i_{p+1}}\right)$. The feasibility constraints are related to the maximum available capacity $q(S) := \sum_{i \in S} q_i \leq Q$ and the single visits per node i.e., $i_b \neq i_k$ for all $1 \leq b \leq k \leq s$. The feasibility feature is examined per cluster of visited customers $S$. A CVRP solution has $|K|$ feasible routes, where each route is created by a unique vehicle $k$ that belongs to $K$. The routes $r_1, r_2 ..., r_{|K|}$ and the clusters that correspond to them, namely $S_1, S_2 ..., S_{|K|}$, constitute a CVRP solution if a) all routes can be achieved and b) the aforementioned clusters form a partition of $N$. The algorithmic tasks of a CVRP are to a) partition the customer set into achievable clustering, and b) to route each vehicle through $\{0\} \cup S_k$, which requires a solution approach similar to the TSP [22, 23], as mentioned in the beginning of this paragraph.

The authors of [21] mention 4 mathematical formulations of the CVRP, 3 compact and 1 extensive and conclude that the extensive is more favorable as it has two important advantages of the compact ones. First, it provides excellent lower bounds (on the required constraints) by linear relaxation solving. Second, the constraints that govern the feasibility issues are an innate part of $\Omega$ , which is the set of achievable routes.

## 2.2. The properties that create the VRP variants

In the same work, the authors have also classified the 6 most important categories of VRPs according to the variants that have emerged in literature during the 50+ years of this knowledge area's history. The categorical distinction is based on a) the **structure of the network** b) the **transportation request type** c) the individual **route constraints** d) the **fleet location and/or composition**, e) the **inter-route constraints** and f) the **optimization objectives**. Other important aspects that seem to arise in many cases relate to the *integration* of logistics and *synchronization* issues.

### 2.2.1. Network Characteristics

The Network Characteristics depend on entities like the delivery end, which can relate to *points in space* (VRP) or *street segments* (ARP) also referred to as links or connections. When mixed, the tasks fall under the family of *General Routing Problems* (or GRPs). Some variations do not rely on the one path shortest of all since this would suggest the neglecting of all the other paths that have a *Pareto-optimal resource consumption*. Also, in real-world scenarios, the shortest (or smaller in various cost terms) path between two points may vary by time. In *dynamic VRPs* it is assumed that some of the data become known during the operation. Also, in some cases the data are known but follow a *probability distribution,* so the VRP is regarded to be *stochastic*. This means that the case of CVRP is considered *static* and *deterministic*.

### 2.2.2. Transportation Request Types

There are many Transportation Request Types apart from CVRP which focuses on the distribution from a single depot to various customers. For example, instead of Delivery there is the Collection, which is often called a *pickup*, where the goods (or waste) move from various points to the depot. Such routing problems may exist in the first stages of a supply chain (e.g. milk collection) or at the end of it (e.g. returned items or waste disposal). This is why the problems **focusing on collection are named *many-to-one*** and the problems **focusing on distribution are named *one-to-many***. Some variants include both ***collection* and *distribution*** (meaning PnD) happening together in a VRP. Another important constraint, called ***backhauling*** is related to the challenge of repositioning and redirecting (rearranging) the items to be loaded in a truck. This constraint is projected as a restriction to the sequence of paying visits to delivery points. If the loading area can be re-arranged (e.g. if the vehicle truck can be accessed from all sides) then the problem is referred to as *VRP with mixed collections and deliveries* or *Mixed VRPB*. There is also the special of *VRP with Simultaneous pickup and delivery* (VRPSPD) where two-direction transportation requests are being served per customer. A common example is the case of beverages and beers where the empty glass bottles can be returned at the time of the delivery of the new ones. A relaxation on the VRPSPD is the *VRP with divisible deliveries and pickups* (VRPDDP) where the visit can be split in two or more, by the same vehicle. This is done to lower the required capacity of the truck by sacrificing some extra movements or the added constraint of specific visit points during the trip of return. The two types of VRPSDP and VRPDDP must not be confused with the VRPs to be presented in the paragraphs that follow.

Another case is not delivering or receiving a packet of goods but rather **visiting** a place or a customer. For example, this is the case for providing a service, like fixing a pipe or taking care of a person (elderly, sick, etc.). These are called *simple visit VRPs*. In case the route points or segments to be visited need to comply to a preset sequence, the problem is called a *VRP with vehicle* ***scheduling***, or VSPs. This class includes many of the problems that relate to the challenges of public transport services.

If the provider of a product can choose between various **alternative routes** (for example a courier that can deliver the packet either to the house, to the work, to the terminal of the courier service or to other pre-selected postboxes and delivery sites) the VRP falls under the class of a *Multi-Vehicle Covering Tour Problem* (MVCTP) since the customer can visit one of many locations to be served.

The *pickup-and-delivery* problems include transportation challenges to or from locations that none is a depot, actually forming routes of ***point-to-point* transports**. This is why the respective problem is mentioned as a *many-to-many* VRP or *Pickup-and-*

*Delivery Problem* (PDP) in general (not to be confused with the VRPSDP or VRPDDP). As to the case of passenger transportation the nomenclature is using the term *Dial-a-Ride Problem* (DARP). The DARPs almost every time include time-window boundaries.

Another common case in the scheduled delivery of goods in **a repetitive fashion**, like the magazine subscriptions, which are called *Periodic* VRPs (PVRP) and for the case of services, include a *visiting pattern*.

An additional case, also quite common, is the repeated supply which occurs in the *Inventory Routing Problems* (IRPs). When compared to other VRP variants these problems hold a fundamental difference which is the lack of customer orders. Instead, the visits are scheduled by the delivery company based on decisions that can guarantee the lowest possible inventory holding costs for their customer and ensure that the latter will not run into any stock-out incidents (*Vendor Managed Inventory* or VMI). The objectives of the IRPs are often found in solutions that try to face common inventory challenges (maximal storage constraints) on *Supply Chain Management* (SCM), like the so-called *bull-whip effect*. The VMI can provide quick and reliable information resulting to shorter lead times and minimal inventory (storage and maintenance) costs. A very common example of such management can be found in fuel delivery to fuel stations.

A variation of the PVRP that is also worth mentioning is the *PVRP with service choice*, which focuses on the frequency of the deliveries, as this has an impact on the demand/service levels. It is regarded as an intermediate between the PVRP and IRP.

Until now, it was assumed that the transportation tasks are non-split. However, **splitting** cannot be avoided when the demand exceeds the available truck capacity. Also, in some cases, splitting allows for a better service and the resulting smaller requests can increase the cost savings. Such a research falls under the *Split Delivery* VRP (SDVRP) umbrella.

Another variation, called **combined shipments**, uses intact transportations but, in contrast to SDVRP, it utilizes several vehicles for the shipment. It also uses various intermediate consolidation points. This practice appears in **multi-modal transportation** which bases its title to the variety of the transfer media (long-distance trucks, plains, ships, smaller vans for the *last-mile* deliveries). Depending on the network structure more variants arise such as *hub-and-spoke* (where the planners create a star-like topology with spokes that presents a complexity of $O(n)$) or *cross-docking*, where the inbound deliveries are directly cross-docked to outbound vehicles. An additional example which is attracting interest for its interesting implementations in the new-coming *city logistics* is the *2-Echelon VRP* (2E-VRP) which includes a delivery (starting from a common depot) being managed through *intermediate depots*, the so-called *satellites*.

A limitation on the vehicles count suggests that there will be transportation requests which will not be completed i.e. only a subset of them will be serviced. So, a proper selection of the ones to be fulfilled may lead to the optimization of the revenues. In the general case, this optimization through route planning can precede the acceptance step and lead to a gain higher than the one compared with the 'first accept, then plan a route' approach. These **Routing with Profits and Service Selection** methods were primarily introduced in the travel salesman problem (TSP) and then were further applied to the VRP. The methods are widely known under the titles *selective (*or *Maximum Collection) TSP/VRP*.

According to the taxonomy proposed by the authors of [24]:

- If the objective includes a mix of routing costs and profits then the problem is referred to as a *Profitable Tour Problem* (PTP) and the respective VRP variant is referred to as *Capacitated PTP* (CPTP).
- If there exists a bound in the route length and the goal is the maximization of profit, the challenge is called *Team Orienteering Problem* (TOP) and the single-vehicle case is simply called an *Orienteering Problem* (OP).
- Lastly, if the objective is the least cost routing with a lower bound on profit, the challenge is called a *Prize-Collecting* VRP (PCVRP), and as before, the case of a single-vehicle is called *Prize-Collecting* TSP (PCTSP).

The recent literature has added a VRP variant where the customers are using their own vehicles or are engaging to a common carrier which offers a fixed-cost service. This variant is referred to as VRP *with Common carrier and/or Private fleet* (VRPPC). Additionally, based on the most recent events, another variant has emerged once again, called *Multiple Vehicle Traveling Purchaser Problem* (MV-TPP) which utilizes service selection. This case requires a set of products and a set of marketplaces where the products are sold after varying price-tags with known demands per case. This challenge requires the calculation of the routes that the capacitated vehicles will select, to visit a subset of point to cover the demand while minimizing the overall purchase cost.

When uncertainty and variability enter the mix, then the challenge turns into **dynamic and stochastic routing**. As it has already been mentioned, the problem is stated as *dynamic* when the information regarding the conditions of the system become known during operation. The problem is stated as *stochastic* when the conditions of the system are uncertain but a function that describes their probability distribution is available. The information that is gradually revealed in dynamic VRP is usually the customer locations and their demands. This is also called an *online* problem. In the stochastic problems the same two dimensions, i.e. the customer demands and locations (translated into travel times) are uncertain. Since some routes may inject delays in the overall service and/or be prematurely terminated, the focus is paid on analyzing the impact in the costs of compensational policies.

#### 2.2.3. Intra-route Constraints

Another important property is the consideration of ***feasibility*** of the VRP variant definition. This is related to the **loading**, the **reusing** of vehicles, the time **scheduling** and the **combinations** of such constraints. The most common are the intra-route constraints which are also called *local constraints*.

The constraints of the capacity are linked with the process of loading/unloading the vehicle, as already explained for the CVRP case. The *capacity* constraints may be *volumetric*, *orientational*, *dimensional* or related to *weight* and *count*. Also, some cases require the arrival of more than one vehicle to the same customer which is called *item clustering constraint*. Another variation is the *Pallet-Packing* VRP, where the 3D boxes have to be stacked onto pallets before their loading to the vehicles. An extra interesting case is the partitioned cases where the VRP requires the use of a fixed *compartmented* logic (VRPC). Furthermore, the items to be used in that case may present an *item-item compatibility* which suggests a flexibility in having them both to proximity or around the same neighborhood or compartment without any issues. On the other hand, some items that do not present *item-compartment compatibility* need to be assigned to different and maybe even distant compartments (like food and toxic chemicals for example). The procedure of loading includes one last very common constraint which requires the use of the Last-In-First-Out (*LIFO*) schema. According to this, the arrangement of the goods can contribute to the minimization of the loading and unloading times, since only a small number of items will need to be re-arranged.

The **route length** is usually related to a constraint of the resource consumed and the problems of that nature are called Distance-constrained CVRP (DCVRPs). The most common bounds of that category are the *spatial distance*, the *route duration*, the *routing costs* or the *count of connections* with some entity.

The **use of multiple vehicles** is researching the cases where the vehicles are able to perform in various routes (during the planning period $T$). The community refers to these problems as VRPs *with multiple vehicle use* (VRPM). For the cases where there is a limited fleet size, the *multiple routes feasibility requirement* suggests that this can happen under the assumption that the vehicles will be reused. It is good to note that when routing with an unlimited fleet in mind, the packing of the route solutions inside the time period $T$ can result to suboptimal decisions. In some scenarios the drivers that work overtime may be permitted under a penalty. Other cases are related to the *multi-trip* VRP (MTVRP) which are applied on city-logistics. This is further utilized under the advent of the alternative-fuel vehicles and the limited (in terms of autonomy) electric vehicles (EVs) which suggests frequent refueling and wider time frames of intermediate waits in the respective stations.

This leads to the very well-known ideas around **time windows and scheduling aspects** which focus on the proper exploitation of the available time windows of opportunity (time slots) considering waiting times, travelling times and service times, in general. This kind of problems has already been mentioned as VRP with Time Windows (VRPTW). A schedule is defined as a combination of start times $T_{ik}$ for the serviced vertex at $i \in V$ when it is accessed by vehicle $k \in K$ is regarded feasible when $a_i \le T_{ik} \le b_i, \forall i \in V, k \in K$. For the condition of vehicle $k$ visiting $i$, the $T_{ik}$ is irrelevant, and $x_{ijk} = 1 \Rightarrow \Rightarrow T_{ik} + t_{ik} \le T_{jk}, \forall (i, j) \in A, k \in K$. The definition shows that arriving at $i$ before $a_i$ is OK. However, arriving later than $b_i$ is not OK. The *service times* are sometimes included in the travel time and the time windows and sometimes explicitly stated as $b_i$. Other problems include the *time-dependent travel times* which are dependent *on the time of the day* and need to be expressed by special *time functions*. Some cases include penalties, like *penalty of early or late services (or both).* Other variants require that the waiting times are bounded. The highest in complexity constraints are the ones modelling driving rules or regulations of schedules (like the EC 561/2006 which restrict the *driving periods*, the *driving times per day*, the *driving times per week*, the *breaks per driving period*, the *rest periods per day*, the *rest periods per week*, etc. All these requirements result to a very tight VRPTW variant in terms of feasibility. Similar constraints, like the ride-time constraint can be found in the DARP for passengers.

### 2.2.4. Fleet Characteristics

Apart from fleets that are based in a single depot there are also cases where the vehicles are stationed to different depots, or own different fleet characteristics and constraints like ***costs***, ***speed***, ***capacity*** and ***accessibility*** to locations. When the fleet is regarded homogeneous but the vehicles are placed in different depots the problem is referred to as **Multiple Depot** VRP (MDVRP). The depots may have a limited capacity in some cases. Also, there is a MDVRP variant where the depots become intermediate refilling/unloading/reloading stations, which is a case that is tightly connected with the multiple use of vehicles that has already been discussed.

On the other side, the category of the **Heterogeneous or mixed Fleet** VRP (HFVRP) refers to groups of vehicles with different values on their versatile characteristics. The same can be the case with the *individual times* which may replace the conventional idea of shared/common/dependent travel times, or the *fixed vs. variable routing costs* and/or *accessible* or *inaccessible* customers. Also, in a similar manner, the routing costs that are vehicle-dependent arise due to the variety of the $c_{ijk}$ for all $(i,j) \in A$. Another issue is whether the vehicle count in the fleet or the groups themselves is bound. For example, this number is limited for the *Heterogeneous* VRP (HVRP) and the *site-dependent* VRP, while the respective count in the *Fleet Size and Mix* VRP (FSM) has no set limit.

Regarding the **Routing of Trucks and Trailers** the respective problem (TTRP) includes at least two types of vehicles; The *Single Trucks* (ST) that have no trailer and the *Truck-and-Trailer combination* (TTC). If there is no maneuvering space at the customer site, the TTCs cannot be used. These customers are called *truck customers* and all the others are called *regular customers*. So, in the general case there are three types of possible routing:

a) An ST route which is serviced by an ST and relates any customer
b) A TTC which is serviced by a TTC but related only regular customers
c) A mixed routing of TTC which is serviced by a TTC but is related to both regular and truck customers.

The TTRP can be enhanced in three ways. Firstly, the costs for the trucks and trailers are set as done in the HFVRP. Secondly, there are optional sites for parking trailers and completing the loading. Thirdly, all locations respect the constraints applied by the time-window requirements. A variation that does not have a fixed assignment to the trailers and trucks is called the VRP with Transshipments and Trailers (VRPTT). This extends the utilization of a trailer as it can be pulled by several trucks on one or more parts of its itinerary. Moreover, there are the support trucks which can serve as mobile depots for the vehicles to be transferrin their load is required. This renders the TTRP a prime case of a VRP with synchronization constraints.

#### 2.2.5. Inter-route Constraints

The inter-route constraints, in contrast to the intra-route constraints which focus on the feasibility of the routing requests given that the routes are properly partitioned, refers to *the global constraints of the whole map*, where the solution depends on how the route and their schedules work when combined.

An example on this can be the ***balancing constraints*** which also aligns with the focus of this work, as such constraints usually emerge from considerations around *fairness issues*.

Another example, which also aligns with the theme of this review, are the *inter-route resource constraints*, which emerge when the vehicles of the given problem need to compete for globally limited resources. The restrictions applied can be the ***vehicle count per depot***, the ***limitation of routes*** that hold a particular characteristic (like long routes, stops count, latencies of arrival etc.) or the ***number of routes*** which pass through (cross) a given area. Another limitation can be applied on the ***processing capacity*** (like the case of postboxes or cut-off times in parcel delivery).

One last example is trying to solve the synchronization issues. This is because the routes and the vehicles scheduling require *an adequate level of coordination*. A primary holistic study on VRPs that abide to Multiple Synchronization constraints (VRPMS) is examined by the author of [25] who offers the categorization of synchronization to follow:

(i) ***Task*** *Synchronization*: a problem of clustering where the tasks can be split by load, volume, periods or vehicles.

(ii) ***Operation*** *Synchronization*: a very common need in project management where each task may be time-related to another one, and the service time may either require two tasks to be performed at the same time or in a series. Similarly, various vehicles in one or various locations may be needed to cover a task with the servicing times coinciding or varying based on dynamic timw-window constraints.

(iii) ***Movement*** *Synchronization*: when two or more vehicles have to move over the same itinerary (like when a truck needs to pull an arriving trailer or the cleaning of snow on a two-lane street).

(iv) ***Load*** *Synchronization*: generated by the need to ensure that all related hardware of the supply chain can serve the amount of the collected/transshipped and delivered load.

(v) ***Resource*** *Synchronization*: working towards the insurance of capacity availability by managing the consumption of the resources.

According to [25] several synchronization types may co-exist and the VRPMs that are mostly studied are the *N-echelon* VRPs and the *location-routing* problems. On the side of the PDPTWs the mostly studied are the variants with *transshipments* and the simultaneous *scheduling* and *vehicle with crew routing* problems.

#### 2.2.6. Objectives

Although the VRPs are usually introduced as challenges that search for solutions aiming to the routing costs minimization, most of the times they are formulated in constructs that aspire to cover multiple goals.

The **Single Objective Optimization** may refer to a simple modification where some of the routing costs are set to zero or to some other, specific value. This is the case that transforms a VRPB and the *site-dependent* VRP to a conventional CVRP. The *Open* VRP does not expect for the vehicles to return to the starting depot (once completing all tasks). Another case may be the selection of maximizing some beneficial/profitable quantity.

For balancing constraints one substitute can be the application of a min-max objective, like for example, the minimization of duration or workload of the toughest route. An important note on the matter, which actually leads the focus of this review, is that any balancing objective, when formulated and considered on its own, makes no sense as the optimally balanced solution may include routes with highly inefficient paths.

The use of **metaheuristics** can in some cases allow for determining the feasibility of solutions to allow (for example due to the response of neighborhood operators) to quickly reach quality solutions. One way of guiding the metaheuristics to feasible solutions faster is through the introduction of ***penalties***. A recent trend is *to add a high merit* in the consideration of the resulting emissions pollution when trying to optimize some aspect of VRPs. These variants are called *green vehicle* (or simply *green*) *routing problems*.

The prioritization of the aspects to be optimized leads to the formulation of **Hierarchical Objectives** as some of the dimensions of the problem (***vehicle count, lengths***, ***durations***, ***completion times*** etc.) may suggest conflicting objectives. A common way is to minimize the vehicle count first and then to move to a second optimization objective.

The **Multi-criteria Optimization** requires the compromise between multiple wishful goals, like the overall routing distance and the balancing of the potential paths, which as an example, is quite similar to the food delivery problem balancing idea that lies under the current literature review.

## 2.3. The algorithms used in solving VRP variants

According to [26], the algorithms that are used in solving the VRP variants found in literature include a wide variety of methodologies, such as:

- *Simulated Annealing* (SA),
- *Deterministic Annealing* (DA),
- *Ant and Fuzzy Ant Colony Optimization* (ACO and FACO),
- *Genetic Algorithms* (GAs),
- *Tabu Search,*
- *Iterative Penalty*,
- *Particle Swarm Optimization* (PSO),

- *Glowworm Swarm Optimization* (GSO),
- *Forward Dynamic Programming*,
- *Constraint Programming,*
- *Linear Integer Programming and Mixed Integer Programming*,
- *Dynamic Dijkstra algorithm*,
- *Column Generation-Based heuristic* (CGB-heuristic),
- *Guided Ejection Search*,
- *Memetic algorithms*,
- *Iterated Local Search* (ILS),
- Hybrid of multistart ILS,
- *Embedded Local Search* (ELS),
- *Adaptive Large Neighborhood* Search (ALNS),
- *Variable Neighborhood Search* (VNS),
- *Iterated Beam Search* (IBS),
- *Branch-and-Bound,*
- *Savings: Clark and Wright,*
- *Cluster-First, Route-Second Algorithms,*
- *Route-First, Cluster-Second Algorithms,*
- *Heuristic Concertation (HC) and*
- various other metaheuristics (apart from GA, SA, Tabu Search).

In some cases, the idea of combining the best properties o,f two or more algorithms has led to approaches like the mix of the tabu search and the VNS, the hybrid of the ACO and the VNS, the hybrid of ACO and Local Search (LS), the hybrid of ACO and 2-opt LS, the hybrid of SA and brand-and-bound, the hybrid of GA and Dynamic Dijkstra algorithm, the hybrid of GA and LS, the hybrid of ILS and *Heuristic Concertation* (HC), the hybrid of multistart ILS and set partitioning, the hybrid of ALNS and the *Embedded Local Search* (ELS) and the hybrid of the *Iterated Beam Search* (IBS) and *Branch-and-Bound*.

Lastly, researchers choose to approach some cases by designs that are based on two (or more) stages of algorithmic calculations. For example, the first stage may minimize the total number of used vehicles and the second the travel distance of the determined routes. Or the first stage may generate (using ILS for example) the best routes without regarding capacity constraints and on the second stage using an algorithm (like Benders decomposition) to determine the solution by the assemblance of routes found in the pool of the 1st stage.

## 2.4. The branching methods (History)

As regards the branching methods that are used to tackle the respective problems, these are classified under the following methods: the **branch-cut-and-price**, the **branch-price-and-cut**, the **branch-and-price** and the **branch-and-cut** algorithms.

According to the historical evolution of the various approaches, as described in [21], the early exact methods were targeted in solving CVRPs. These are actually extensions of the TSP reduced to the challenge of finding the Hamiltonian path that visits -exactly once- all the given points, with a minimum cost.

### 2.4.1. Brand-and-Bound Algorithms

A tremendous progress was noted with the introduction of the **direct tree-search** method around 70s but this was still the beginning. Somewhere around the 80s the tree-search algorithms were substituted with the **Branch-and-Bound** which incorporated relaxations deriving from the *Assignment Problem* (AP) or the *Shortest Spanning Tree* (SST). These problems could provide solutions to instances that were covering scenarios with a few tens of customers.

### 2.4.2. Matching and Assignment

Around the end of the 90s the bounds that were proposed were more elegant, like the **Lagrangian relaxations** (a method of decomposition) and the **Additive approach**. This enhanced the direct tree search performance leading it to its highest, at least, until the appearance of the cutting planes. The first reduction strategies were achieved as Bounds based on **Assignment and Matching**.

According to the first experimental evaluations of [27], the relaxation that was performed on a symmetric model (9 test instances including 44 to 199 customers) presented a *b-Matching* with an average ratio approx. 77% of the corresponding bound when compared to the best-known value. The simpler AP bound had a performance of approximately 67% for symmetric instances. A similar evaluation, which was examining asymmetric instances up to 70 customers, presented a *b-Matching* ratio of around 91%.

### 2.4.3. Shortest Paths and Spanning Trees

The next strategies included Bounds based on **Shortest Paths and Spanning Trees**. The primary direction was focused in the 1-tree relaxation use, which then was extended to a *K-tree* research (applied mainly on the symmetric and asymmetric variants of the CVRP, the SCVRP and ACVRP). Another tree-based relaxation led to the *k-Degree Center Tree* (k-DCT) which is a tree of degree $k$ at vertex 0, where $k$ is between $|K|$ and $2|K|$.

The Lagrangian bound was created by dualizing the degree constraints. The next important SCVRP relaxation was based on *q-route* that refers to a route with load = $q$, not including two-vertex loops. An enhanced version, the *through q-route* was created by selecting the two shortest paths that start from the depot and reach point (customer) $i$. The q-route as a concept is being used in the recent works of the Branch-and-Cut-and-Price algorithms which perform as the best exact solutions for the CVRP.

### 2.4.4. Lagrangian and Additive Approaches

The **Additive** approaches allow for the combination of various lower bound ideas, which may result to considerable better performance in some cases. However, the anticipated results may vary until a number of scenarios is tested. For example, in [28] a ACVRP solution (random instances), consisting of 300 delivery points and 4 vehicles took about 10 secs in a 5.3 Mflops PC, when different combined relaxations based on q-routes and shortest paths on [29] resulted on a lower bound that permitted the solutions of 50 delivery points scenarios in about 12 hours on a 12 Mflops PC.

### 2.4.5. Structure of Branch-and-Bound Algorithms

One very important ingredient that is crucial to the success of a Branch-and-Bound implementation is the **Branching Scheme**. This can be based on *branching on arcs*, *branching on customers* or a mixed branch scheme or other specialized methods like the branching rule that was used for the asymmetric TSP called as the *sub-tour elimination.* The algorithms that aspire to solve a CVRP in the general case adopt a strategy of best-bound-first. This is due to the fact that the branching is run on the pending node of the tree with the lowest bound value. This rule can facilitate the minimization of the subproblems that require higher memory utilization for a solution, which in computational terms has proved to outperform the depth-first strategy (as the branching node selection is LIFO rule based).

The evolution of the branching methods led to several rules being programmed to remove arcs which cannot be part of the solution. This **reduction** is blocking their use and thus allows for the early detection of **dominance** relations. Such rules are called *reduction rules* and can be used either on the entirety or on parts of the problem.

### 2.4.6. Branch-and-Cut Algorithms

The early branch-and-cut algorithms were based on the idea of a SCVRP two-index formulation (VRP2). The first case (of Augerat, in 1995 [30]) included inequalities not found in the model. The four inequalities are related to i) the ***rounded capacity***, ii) the ***generalized capacity***, iii) the ***comb*** and iv) the ***hypotour***. After a series of experiments on various branching schemes, using various criterions, Augerat concluded that the best strategy is finding the best set of vertices ***S*** by checking each simple strategy considered. In 2003, another Branch-and-Cut approach was created, based on separating the capacity constraints by using three heuristics. These helped the algorithmic identification of violated capacity inequalities and to decide how to branch while expressing the solution as a convex combination of Hamiltonian cycles. In 2004, a new schema on separation procedures was used for the already known inequalities (a similar but enhanced idea to the ones created by Augerat).

The **Families of Cuts** are classified based on the following properties: the *TSP-Related Valid Inequalities*, the *Capacity Constraints*, the *Framed Capacity Inequalities*, the *Comb Inequalities* (for the symmetric TSP), the *Hypotour Inequalities* (for subnetworks of ***G*** that have no feasible CVRP solutions) and the ***Multistar Inequalities*** (for the CVRP with unit demands).

### 2.4.7. VRP variants grouped by constraint type

Table 1 collects and groups the main VRP archetypes and variants that have been mentioned in chapter 2, according to the type of their constraints. The 1st column titles describe the main constraints types and in parenthesis the key defining properties. The 2nd column holds the variant's abbreviation and the 3rd holds a brief description.

**Table 1.** Archetypes and variants of VRPs grouped by constraint type

| Constraints (and key properties) | Code | Brief information on the VRP variant |
|---|---|---|
| **Network Structure (point in space, street segments)** | | |
| Vehicle Routing Problem | **VRP** | The emerging requests are found in specific street points |
| Arc Routing Problem | **ARP** | The emerging requests are found along street segments or road networks |
| General Routing Problem | **GRP** | A mix of VRP and ARP |
| **Transportation Request Type (1toM, Mto1, MtoM, backhauling, visiting, vehicle scheduling, patterns, splitting, bundles)** | | |
| Pickup & Delivery (PD) Problem | **PDP** | Picking up from one place and delivering to another (many-to-many VRPs - static & deterministic) |
| Dynamic PDP | **DPDP** | Re-shaping of the dominating routes |
| Dynamic and Stochastic PDP | **DSPDP** | Re-shaping of the dominating routes while the algorithm adapts to stochastic changes |
| Capacitated VRP | **CVRP** | The vehicles' capacitance falls under symmetric and asymmetric constraints (SCVRP, ACVRP) |
| VRP with mixed deliveries and collections | **Mxd-VRPB** | The loading area can be re-arranged |
| VRP with Simultaneous PDs | **VRPSPD** | Two-direction transportation requests are being served per customer (e.g., beer bottles) |
| VRP with divisible PDs | **VRPDDP** | The visit can be split in two or more, by the same vehicle |
| Simple visit VRP | **VRPwSV** | Visiting to provide service, not goods (e.g., plumber or elder care) |
| VRP with vehicle scheduling | **VSP** | Points or segments to be visited need to comply to a preset sequence |
| Multi-Vehicle Covering Tour Problem | **MVCTP** | Choosing between various alternative routes |
| Dial-a-Ride Problem | **DARP** | Passenger transportation (almost all variants include time-window boundaries) |
| Periodic VRP | **PVRP** | Delivery of goods in a repetitive fashion (e.g., magazines) |
| Inventory Routing Problem | **IRP** | Visits are scheduled - no customer orders |
| PVRP with Service Choice | **PVRPwSC** | Focuses on delivery frequency (something between PVRP and IRP) |
| Split Delivery VRP | **SDVRP** | Transportation tasks are split |
| Split Delivery VRP with combined shipments | **SDVRPwCS** | Utilizes several vehicles for shipment (found in last-mile deliveries/hub'n'spoke/cross-docking) |
| 2-Echelon VRP | **2E-VRP** | a delivery being managed through intermediate depots, the so-called satellites. |
| **Selective (or Max Collection) TSP/VRP** | | Limitation on the number of vehicles |
| Capacitated PTP | **CPTP** | The objective includes a combination of the routing costs and the profits |
| (Team) Orienteering Problem | **TOP / OP** | The route length is bounded with the goal of profit maximization |
| Prize-Collecting VRP | **PCVRP** | The objective is the least cost routing with a lower bound on profit |

| | | |
|---|---|---|
| VRP with Private fleet and Common carrier | **VRPPC** | Customers use own vehicles or get assigned to a common carrier (usually w. a fixed-cost service) |
| Multiple Vehicle Traveling Purchaser Problem | **MV-TPP** | Utilizes service selection (a set of marketplaces or a set of goods - visit a subset to cover demand) |

**Intra-route Constraints (feasibility, loading, reusing vehicles, time scheduling, combinations, multiple vehicles)**

| | | |
|---|---|---|
| VRP with Time Windows | **VRPTW** | The service time-frame falls under constraints |
| Pallet-Packing VRP | **PPVRP** | The 3D boxes have to be stacked onto pallets before their loading to the vehicles |
| VRP with compartmented logic | **VRPC** | The VRP requires the use of a fixed compartmented logic |
| Distance-constrained CVRP | **DCVRP** | Constrained by spatial distance, route duration, routing costs or the count of connections |
| VRPs with multiple use of vehicles | **VRPM** | Vehicles are able to perform in various routes |
| Multi-trip VRP | **MTVRP** | Utilized mostly for the alternative-fuel vehicles and the limited autonomy electric vehicles (EVs) |

**Fleet Composition or Location (costs, speed, capacity, accessibility, multiple depots, fleet gene)**

| | | |
|---|---|---|
| Multiple Depot VRP | **MDVRP** | The fleet is regarded homogeneous but the vehicles are placed in different depots |
| Heterogeneous or mixed Fleet VRP | **HFVRP** | For groups of vehicles with different values on their versatile characteristics |
| Fleet Size and Mix VRP | **FSM** | No set limit in fleet size, site or type(s) of vehicles |
| Routing of Trucks and Trailers | **TTRP** | VRP with synchronization constraints (for single trucks and truck-trailer combination) |
| VRP with Trailers and Transshipments | **VRPTT** | TRP that has no fixed assignment to the trailers and truck |

**Inter-route contrainsts (holistic, balancing)**

| | | |
|---|---|---|
| VRP with Multiple Synchronization constraints | **VRPMS** | VRPs requiring synchronization on at least one of: Task, Operation, Movement, Load, Resource |
| PDP with Time Windows | **PDPTW** | Includes variants with transshipments and the simultaneous scheduling and vehicle with crew routing |
| N-Echelon VRP | **NE-VRP** | Similar to 2E-VRP |

**Optimization Objectives (prioritization, multi-criteria)**

| | | |
|---|---|---|
| Open VRP | **OVRP** | No need for vehicle to return to the depot after servicing the last customer |
| Green VRP | **GVRP** | Considering the resulting emissions pollution when trying to optimize some other aspect of VRPs |

# 3. A review of the works contributing in the delivery industry

## 3.1. Logistic Problems of the Supply Chain in Food Industry

### 3.1.1. Inventory Control Policy in Perishable Food Supply Chain

The authors of [31] made an important contribution on minimizing the waste and losses found in the perishable Food Supply Chains by their research on *inventory control strategies* (ICS). Then, they introduced the Basestock-Constant Work-In-Progress (the B-CONWIP), a pull-based ICS, which they then compared with two existing policies. The challenge that they had to address was to find a way to minimize total cost (i.e. the storing, deterioration, shortage and ordering) without risking customer service levels. Their objective was to follow a lean policy while refining the attributes that lead replenishment decisions. They found out that apart from *stock level*, and *age information*, the *demand information*, that was not taken into consideration on previous works, had a huge impact on minimizing the total costs, as it allows for the perishable products to be produced close to the anticipated periods of demand. The results suggest lower costs by 47.4% and 20.4% while keeping the same service level (99%). The authors suggest that they are many factors that need to be considered before generalizing these findings. These factors relate to the shelf lives of the food products per case, their demand patterns, their production numbers and ordering cost.

### 3.1.2. Economic Order Quantity for growing items

In accordance to the findings of the previous work, the authors of [32] examine the factors that affect the *Economic Order Quantity* (EOQ) and how these relate to the *Economic Production Quantity* (EPQ). Their goal is to determine the EOQ for the case of newborn animals, according to the annual demand while maximizing profits. The total costs in the problem formulation involve purchasing costs, feeding costs, holding and total set-up costs. The objective function includes, as expected, both the EOQ and the overall profits. The findings show that the EOQ of the hatches is mainly affected by the holding and set-up costs, while the total profits are affected by all costs and mostly the feeding costs. The study provides a generic model for any good that can be grown and/or fed, providing important insights on the respective inventories of such applications. The authors recommend the inclusion (in future work) of shortage occurrence and the introduction of a variety on the types of goods to be managed.

### 3.1.3. Hub Location Optimization for Products with Uncertain Demand

On that note, following the issues mentioned in 3.1.2, the authors of [33] work on the hub positioning problem. The optimal location can facilitate minimizing the costs mentioned on 3.1.2. However, picking the best site is not easy, due to the variety of the perishability of the products to be stocked, and to the uncertainty of demand. The problem is approached by using Lagrangian relaxation to an uncapacitated hub at first, and then to a capacitated one with very interesting results. The proposed models can help the decision maker in determining the best site and volume of products (agricultural in this case) to be selected, in respect to his/her risk aversion level. The solution to this problem can provide useful feedback for the initial positions of riders, in any VRP of that nature.

### 3.1.4. Collection of different types of goods under Uncertainty

A similar uncertainty is observed during the collection of goods from various sites (farms and milk collection centers for example) for delivering to a central facility. Due to the variety of types of goods to be collected and transferred, this challenge includes various logistics costs which can increase significantly under an environment of uncertainty. The authors of [34] propose a model which includes split deliveries, for uncertain demand, service time and vehicle speed. The core problem is solved under different scenarios of risk assessment through the implementation of a heuristic called the *enhanced iterative local search*. The case study reveals that the uncertainty level is very critical and drastically affects the form of the optimal collection-network design. As regards the ideas on future-work, the authors suggest focusing on constraints related to farm-vehicle time windows and farm-vehicle compatibility.

### 3.1.5. Fresh food sustainable distribution

As regards the multi-dimensional objectives, the work in [35] aspires to tackle a threefold optimization challenge regarding the minimization of *cost*, delivery *times* and *carbon footprint* in the Fresh Food Distribution Networks (FFDN). One of the key features of that work is the geographically distributed market demand and the production capacities of the respective points of interest, which has direct similarities with the requirements of the current review theme. The work of [35] is placed around the design of an expert system that is called Food Distribution Planner (FDP) that uses a *Linear Programming* (LP) tool considering the perishability of the goods and the idea of multi-modal transports. The conceptual design is presented in Figure 2.

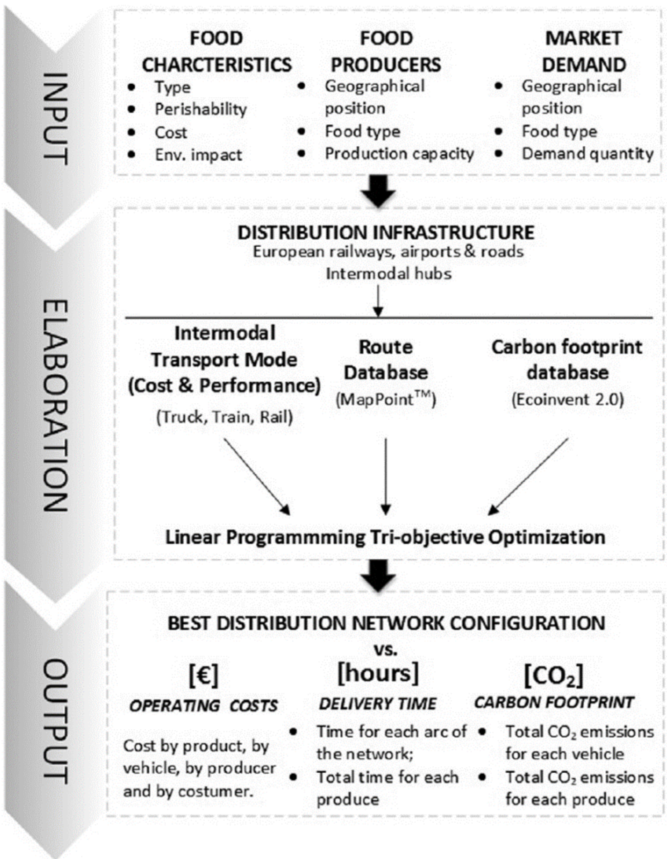



**Figure 2.** **FDP Architecture [35].**

The design is applied on a real case study and the first results suggest that the three optimizations cannot coincide in a close neighborhood. For example, the optimization of operating cost leads to a significant delivery time and carbon footprint which globally worsens around 233 %. Similar results emerge when considering the delivery time and footprint optimal solutions. This led to the use of the normalized normal constraint method which reveals the ***Pareto frontier*** of all the non-dominated solutions, as shown in Figure 3. The final solution is selected from this set either manually or by an arbitrary method which will converge according to some empiric rule or the parameters imposed by the expert system user. The results of the actual study showed that the solution that was selected could aim for a 9.6% carbon footprint reduction with a 2.7% increase in operating costs. The authors suggest that a future research, based on a *Mixed Integer Linear Programming* (MILP) tool, should consider the installation costs and emissions of all production and *Intermodal Hubs* (IHs).

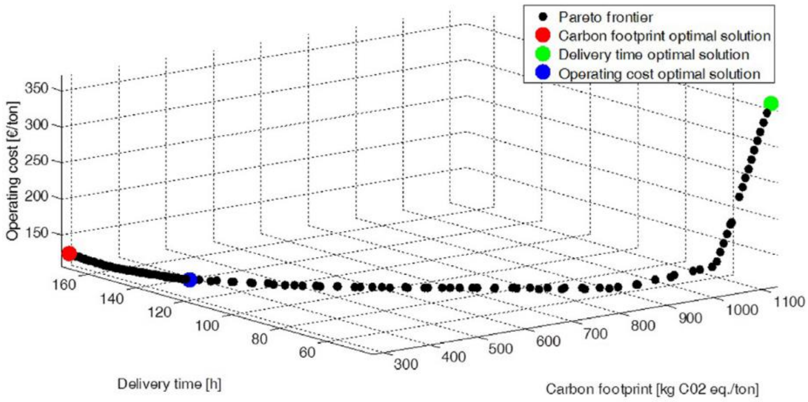



**Figure 3. Pareto frontier of all the non-dominated solutions, including the optimal ones per objective [35].**

#### 3.1.6. On-demand Grocery Delivery Optimization Framework

The work of [36] aspires to minimize the *Cost Per Delivery* (CPD) and at the same time to maximize the *Customer Experience* (CX) by using a two-stage optimization model. The 1st stage includes a *Last-Mile* (LM) optimization which is expressed as a PDPTW. A *Just-In-Time* (JIT) heuristic is used to minimize the waiting times. The 2nd stage used a multi-objective design to trade-off between the CPD and CX, solving the *First-Mile* (FM) problem. The work proves that the dynamic PDPTW can ensure adequate savings in CPD, while keeping CX in a good level, which means by servicing the customer within a pre-specified time (as promised by a Service Level Agreement or SLA).

#### 3.1.7. Green-Fresh Food Optimization on Heterogeneous Fleet VRP using a GA

The algorithmic tool that was created in [37] aims to reduce the costs of the Fresh Food distribution while managing to tackle the demanding nature of the Green Fresh Food Logistics with *Heterogeneous Fleet Vehicle* (GFLHF-VRP) through a sophisticated GA variation. This GA includes the *Adaptive Simulated Annealing Mutation* (GAASAM) which, as the name suggests, manages to operate in an adaptive way, lowering the total distribution costs and subsequently the goal of lower fuel consumption and thus carbon emissions. Furthermore, the GAASAM design is universal enough that it can provide a managerial platform for all the enterprises that face GFLHF-VRPs. The tool can help these enterprises to arrange their distribution projects, planning with multiple types of vehicles in mind, while operating at a higher social responsibility level.

## 3.2. Routing Problems in Food Industry

### 3.2.1. The Perishable Inventory Routing Problem (PIRP) – A review

In perfect alignment with the purpose of the current review, the work of [38] begins by expressing the importance of integrating the inventory management procedures with the vehicle routing decisions, rather than treating them as separate problems. The same concept can -and should- be generalized when possible, as it can lead to solutions that are better than the results of the merging of the solutions of the individual subproblems. Since this issue is prominent it has become the center of extensive research during the recent years, especially for the perishable products where the need for the best possible service is higher. Figure 4 collects and classifies the types of products found in the respective literature.

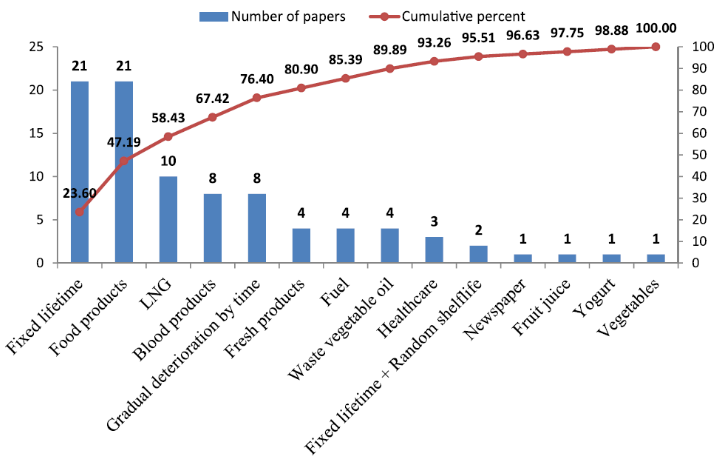



**Figure 4. Types of perishable products in the PIRP literature [38].**

Primarily, the analysis shows that only a few papers have studied such problems, when considering the uncovered areas of their works. For example, the 2/3 of the papers examine the case of single products which makes the investigation easier but reduces the practical interest. Also, the demand is easy to be considered deterministic but this can be realistic in a bounded space. Finally, it is more realistic to search for challenges that crave multi-objective solutions, so in overall, it is strongly recommended to:

*(i)* *study and cover the multiple product scenarios,*

*(ii)* *model systems and design methodologies and algorithms that confront real-world uncertainties and, lastly*

*(iii)* *try and cover multiple objectives at once.*

Based on the findings of [38], the exact solution methodologies are less than the approximate ones. Most use existing software to solve medium-sized challenges, so it is recommended **to code novel algorithms and most preferably exact ones**. Also, the authors of [38] expect that **more matheuristic solution approaches** will be developed in the future. As to the deterioration rate property, it is advised to **use a non-linear function** that will resemble a real-world challenge. Also, it would be helpful if more work was created around the **multi-depot PIRP cases** and on **case-studies in general** as they provide better insights for understanding the nature of a paper's contribution. Another element that would be beneficial as an addition is the **pricing of the perishable products**, as it is closely connected with that specific quality (perishability). It will also be good for the future researchers to include more **evolutionary algorithms**, as in 3.1.7 for example, since they will be able to address **multiple objectives**. Finally, it would be nice to generate works on algorithms **designed to overcome disruptive effects**, and solutions that recover and prove the robustness of a supply chain during widespread accidents.

### 3.2.2. Multi-objective VRP for perishable items

Focusing on the actual VRPs for perishable items, the study of [39] aims to minimize the degradation of the quality of perishable items along with delivery costs. The trade-off to be established between the final quality of the items in respect to the final delivery cost is served by considering the cases of refrigerated vs. general purpose vehicles. The customers are split into two categories depending on their location and type of vehicle.

The research hypothesizes that the demands are known a-priori and that the refrigerated vehicle's capacity is higher than the generic type and also has a homogeneous capacity.

The authors use two solution approaches, the *Non-dominated Sorting GA* (NSGAII) and the *Strength Pareto Evolutionary Algorithm* (SPEA2) and analyze the results with various performance metrics concluding that the former outperforms the latter. As for the future work, the authors wish to research other types of distribution networks and other important objectives.

### 3.2.3. Multi-depot perishable VRP with mixed time windows in cold chain logistics

The work in [40] focuses on the “cold chain” logistics, by trying to improve the delivery quality of products and keep customer satisfaction on a high level. In order to achieve this, the goal is to plan a reasonable path of distribution that will serve the refrigerated trucks that move across multiple distribution centers by minimizing the costs as much as possible while retaining service quality. This challenge falls under the *multi-depot VRP with mixed time windows* (MDVRPMTW). The complexity is reduced by using clustering and sorting to initialize the population. Then, a *Hybrid Partheno-GA* (HPGA) is proposed to adjust the assignment of the customers and improve performance.

The results of a real case study show that the solution in cold chain cases differ from the conventional VRP solution since the former selects a clear detour as it focuses in the deterioration reduction and the minimization of the time window costs. This is a finding that the logistic companies need to consider when planning routes for such a problem.

Although the work is quite mature there are a number of drawbacks that still remain and the authors call for improvement in future work. An important one is the a-priory knowledge of the customer demands. The second is that the deterioration costs in this work only vary with distance and door-opening time although under real conditions they get affected by the temperature differences between the ambient environment and the refrigerator.

### 3.2.4. Bi-objective optimization of e-grocery deliveries

Similar to the aforementioned works, the authors of [41] focus in reducing food waste by minimizing travel distance while keeping food quality high. The orders are picked from various stores and then delivered to the customers. The formulation of this challenge is expressed as a dial-a-ride problem, with a twist, as the procedure decides which store to be used for picking the products, according to their inventory levels. The results, once again, show that there is a substantial tradeoff between food quality loss and travel distance reduction.

Two important issues regarding future work relate to a) the inclusion of peak-times, congestion incidents and parking availability, and b) the consideration of **dynamic settings** where the decisions regarding the store-assignment may have negative side-effects on the sorting of future orders.

#### 3.2.5. VRP with time-windows for perishable food delivery

The authors of [42] take into consideration the randomness of the perishable food delivery challenge, thus constructing a *stochastic VRP with time windows* (SVRPTW) model which they use to get the optimal routes, the loads the fleet dispatching and the proper departure times (from a single depot to various locations). They also make references to the variability of temperatures and travel times which modify the objective functions and the constraints expressed in the models. The results indicate that a) the energy costs and b) the inventory, influence the total delivery costs. Also, it was discovered that there is a trade-off between the fixed costs of vehicle dispatching and storage (inventory) costs, which demonstrates that using less vehicles can reduce fixed costs but increases the inventory ones. The constructed model yielded better results than the conventional VRPTW. As anticipated, the stochastic travel times required more vehicles to cover the customers' needs. The softer constraints on time windows led to a smaller fleet requirement, however it came with higher inventory and penalty costs. Finally, the models that considered the time and temperature dependencies resulted in lower delivery costs, lower inventory, energy and transportation costs.

### 3.3. Customer Preferences and Behavior

#### 3.3.1. Customer Preference in Food Delivery Services

A very important contribution into better understanding the Food Delivery Service consumer problems and how it can be improved, is given in the work of [43]. This work outlines the needs and preferences from the consumer side of view which plays a crucial role in the decision-making process that takes place when examining various factors like *reliability*, *preference*, *liking* etc. The research was based on primary data, using a questionnaire on a sample size of 169 people, out of which responded the 84.5 %. The data was processed using the gray analysis technique. The online food services are characterized by three dimensions; the *taste* of the food, *quality* and the *delivery* *services*. More than half of the population regarded taste to be the most important one. The quality and the delivery were very close, so about a quarter for each. According to the responses the price for the premium of taste is regarded as very reasonable. As to the brands (Swiggy, Foodpanda, Zomato etc.) the majority responded 'others' (the 4$^{th}$ option) and the analysis of the rest of the data revealed that in spite of the existence of many trustworthy brands the people want something 'unique'. When focusing on what would provide satisfaction to the customers in order to build the most popular brand, the people replied about hygiene in the kitchen and delivery-related issues. In terms of cuisine preference, half of the population replied Indian and most would consume it during the evening. The study concludes that apart from the factors that have been mentioned, other factors, like service quality, image, reputation, corporate image (branding), perceived value, and behavioral intensions are very important in customer loyalty and consequently customer retention.

#### 3.3.2. Food Supply Chain design based on customer satisfaction under uncertainty

The work of [44] is a fair and well-rounded attempt to approach Food Supply Chain design in the most realistic way possible. Its main focus is to minimize the tardiness and/or earliness of deliveries to customers while maximizing the delivered product quality. The purpose of this is, as expected, to maximize customer satisfaction. The design of the study is constructed so that it will be as realistic as possible by embedding all the decisions of the different phases and modules of a food supply chain under uncertainty. For example, regarding the supplier side, the design considers this to be served as a multi-commodity since no single supplier can provide all the food. As to the vehicles, the fleet is considered to be heterogeneous and acting as in a VRP, presenting various carrying capacities and speeds. The vehicle preparation time is also considered a variable. It is also acknowledged that since the orders need more than one vehicle to be carried, it is best to transport each product by a dedicated type of vehicle in each case, where needed. Finally, as to the travel times, these are taken into account as triangular fuzzy. Finally, the end-users can be found in fixed geographical locations with a specific amount of demand for each, assigned under a time windows like (x,y) for each customer.

The methodology that is used lays on meta-heuristic algorithms **since it has been shown that an exact method is not able to provide a solution to a large-scale problem within a reasonable timeframe**. So, the authors of this work used the MOTTH algorithm which is based on a genetic algorithm and a mathematical model that uses the augmented $\boldsymbol{\varepsilon}$ constraint.

The investigation of this work confirmed that an increase in the quality of the products affects the sum of tardiness and/or earliness of the customer deliveries. This means that it is up to the company to establish its preference in weighting terms for the two objective functions. It was also shown that the MOTTH algorithm outperforms the NSGAII. A last practical suggestion mentions the use of compartmented refrigerators so that the opening of one that is emptied does not influence the rest of the products.

### 3.3.3. Service Quality, Customer Satisfaction and Loyalty (in Fast-Food Industry)

The work in [45] describes the findings of a research that was conducted on 197 samples from customers of leading Fast-Food enterprises, located in Taiwan. This research shows that the improvement of service quality influences the customer satisfaction in a positive way and then, through this satisfaction, the customers are developing customer loyalty.

## 3.4. On line food Apps and Aggregators

### 3.4.1. Customer Trust in Mobile Food Delivery Apps (MFDA)

In the paper of [46], a wide research is done regarding the *Technology Acceptance Model* (TAM) factors, the *Mobile Service Quality* (M-SERQUAL) factors and the *behavioral drivers on personalization/privacy* and how these all affect their trust and subsequently their loyalty in *Mobile Food Delivery Apps* (MFDA). In total, 494 valid records were collected and analyzed using the *Partial Least Squares-based* (PLS) technique with *Structured Equation Modeling* (SEM).

The results showed that TAM factors (**regarding ease of use**), M-SERQUAL factors (regarding **information quality** and user interface and experience i.e., **UI/UX**), and **personalization** have a positive correlation with trust in MFDAs which also has a positive correlation with **loyalty** to MFDAs.

An important finding is that trust appears as a mediator to the effects of the TAM and M-SERQUAL factors, and personalization on the loyalty expressed by the customers (creating a closed loop of causality). At the same time, the **privacy** had a small correlation factor, meaning that is seems unrelated to customer loyalty.

### 3.4.2. Loyalty toward online Food Delivery Service

In addition to the research of 3.4.1, the authors of [47] study the direct influence that food quality and e-services quality have on customer loyalty and any indirect effects that this may have through the mediating factors of customer satisfaction and perception of *Online Food Delivery* (OFD) value. The sample of the study was 405 customers and the data were analyzed using the variance-based SEM technique.

The results confirm the direct influence of food quality to online customer loyalty. However, no high correlation was observed between e-service quality and online loyalty. Similar to the findings of 3.4.1, this study reveals that perceived value and customer satisfaction present a mediation role between both food quality and e-service quality on the online customer loyalty.

### 3.4.3. Online Food Delivery Aggregator Apps (Dining Perception & Online Orders)

Ever since the advent of affordable smart mobile devices, the *Online Food-Delivery Aggregators* (OFAs) have been gaining popularity which, in turn, has become a key distribution channel for food suppliers and restaurants. This is why the authors of [48] focus on the examination of the ways that the OFA mobile Apps affect the transaction reliability of order booking, **based on the customer's cognitive and affective states** during a diner and their subsequent behavior.

The collected data came from 458 respondents and were analyzed using SEM. The work utilizes a) the *Cognitive Valence Theory* (CVT), which suggests that individuals experience psychological arousal when confronted with highly immediate nonverbal messages, b) the *Stimulus-Organism-Response* (SOR) theory, which suggests that stimulus is the impulse that contains statement, organism is the individual and response is the effects, reaction or answer, and c) the *cue theory*.

According to the findings of the research, product presentation and usability are good predictors of reliability in transactions and thus, key mobile App attributes for OFA. This relationship is greater for women. Additionally, richness of media stimulants leads to positive feeling about the product, so the presentation on screen enhances the perception of availability of the product. The abundancy of products helps the ease of searching on a mobile screen. Lastly, being up to date is also an important factor.

#### 3.4.4. Predicting Satisfaction and Intentions on Online Food Delivery (OFD)

The study of [49] investigates the intentions of the customers who use *Online Food Delivery* (OFD) services by evaluating satisfaction, food quality, and e-service quality. The assessed dimensions of the OFD quality include: *service convenience*, *customer service*, *service completion* (fulfillment), and *perceived control*. The findings suggest that customer service, control, service fulfillment and food quality are all positively correlated with the customer satisfaction in OFD services.

As it has already been established by the previous works of 3.4.1 to 3.4.3 for Asia, Indonesia and India, respectively, the Americans seem to project the same strong positive influence of customer satisfaction that lead to the loop-back enhancement of their behavioral intentions to order through OFD, confirming that the aforementioned OFD dimensions can indeed operate as strong predictors for the customer intentions on using the OFD Apps.

#### 3.4.5. Online Food Delivery Apps (OFDAs) Adoption during Covid-19 pandemic

The two paragraphs to follow will focus on two researches related to the understanding of the consumer's behavioral intentions during the Covid-19 pandemic (given the OFDAs on-demand increment). As the authors of [50] state, the perceived trust in the OFDAs information had played an important moderating role on their adoption of the services. In total, 246 users participated in the study of [50], through email and the primary data were analyzed using PLS-3.

The research of [50] provides 12 key insights into OFDAs adoption through the customer's behavioral intention. It was found that the information and the attributes related to food service have a direct effect on the perceived usefulness of OFDAs as they shape the user's intention of use. Also, vice-versa the user's behavioral intent in relation to the service and the customer's perceived trust both play an important role on the adoption of the OFD services. Regarding demographics, the data show that women, educated users, young university students, and people with middle to high income are more prone to use OFDAs. A **key factor that closes the gap between purchase and actual**

**usage is the perceived trust**. This is an important hint that needs to be properly exploited by the company managers of the respective OFDAs. Communication to the proper market segment for that matter is crucial and the information to be shared needs to be of ***good quality***, ***highly available***, ***easily shareable*** and ***credible***. These properties have strong and positive influence in increasing the customer's desire to use the OFDA. Better-quality food and deals encourage the use of OFDAs, rendering them more widespread.

#### 3.4.6. Using Mobile Food Delivery Apps during Covid-19 pandemic

The second research on this subject was conducted by the authors of [51] who examined how are the consumers engaging into the mobile FDAs (MFDAs) during the Covid-19 pandemic. In total, 432 users participated in the research. The data were analyzed using SEM through the application of the *Theory of Planned Behavior* (TPB).

The results highlighted that the ***behavioral control***, the ***dining attitudes***, ***subjective norms*** (i.e. the response of an individual while enduring social group pressure factors) and the ***delivery hygiene*** were the main drivers that led to the adoption (and continuance) of the MFDAs. As to ***food safety***, it was correlated to ***behavioral intention*** while the ***social isolation*** was correlated to ***continuance intention***. In addition, the behavioral intention acted as a mediator of the impact of the aforementioned dimensions (*food safety*, *attitude*, *delivery hygiene*, *behavioral control*), almost as a self-reference, on the continuance intention.

### 3.5. Governmental and Regulatory Compliance

The authors of [52], being inspired by real-life examples, have decided to study the trade-offs between ***product performance***, ***reliability***, ***time-to-market*** decisions and the ***impact on governmental directions and regulations***. As expected, the product reliability is minimal for highly innovative products, due to the adoption rate of novel technologies. However, it improves significantly if the entrepreneurs decide to spend for a longer time-to-market entrance.

The framework that the authors create examines when a firm should decide to launch a low- or high-novelty product and will what development life-cycle (long or short) to select. The idea is to study what are the impacts of a government's regulations on the firm, on the product line (or product mix) and the customers when a *Minimum Product Reliability Standard* (MPRS) is followed.

The results show that the regulation can be the cause of product reliability, product availability, product research or it can improve the company's profit, which all, in principle oppose to the anticipated outcome of a qualified legislator/regulator. In order to shed more light into this paradox, the authors examine the case from all stakeholders' view. From the company's perspective there are two effects taking place at the same time. The first is the **emerging burden of compliance**. In contrast, the second effect, in case of a committed company, **can be leveraged to produce a reliable product** and consequently a competitive brand (in the long run).

This, in turn, forms the customer beliefs which further improves the perceived product reliability. The cost and commitment effects thus lead to the regulation effect depending on specific circumstances.

From the perspective of a legislator/regulator, the view is broader, including the opportunity for the establishment of **new industry standards**, which, when aligned with the strategic decision of all related players, this can co-jointly lead to profit optimization given that all will eventually need to follow the imposed product regulations.

Regarding the completeness of the work described in [52], the authors mention that there are a few important points to be taken into consideration. The one is related to the **implications to the purchasing group dynamics** which influence the customers' behavior. The second is the fact that the specific model framework includes a few limitations, as the **issues that may arise in a multi-competitional environment**. Also, the decision variables include only a few discrete choices (low/high, short/long), so the use of continuous decision is advised as it is expected to strengthen the model. Third the long periods of product development **may (or may not) include the emergence of enhanced product innovation** which would be nice to be included as an option. Finally, the study on the MPRS is examined thoroughly, however it is **left unsolved in respect to the government's optimization problem**. However, the social welfare is expected to increase in the case of legislative governmental intervention.

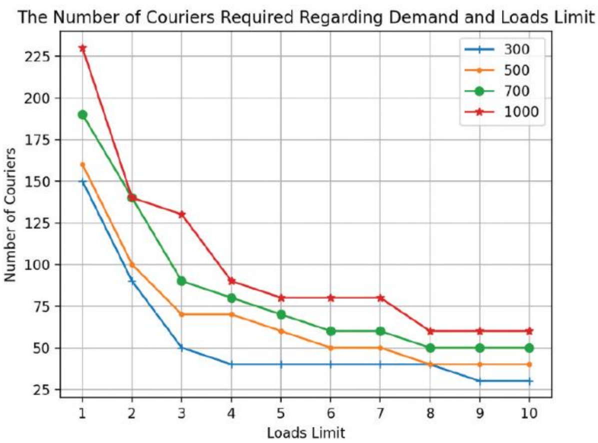
### 3.6. Decision Support Systems in Food Supply Management

#### 3.6.1. Online Food Ordering Delivery Strategies (multi-agent models)

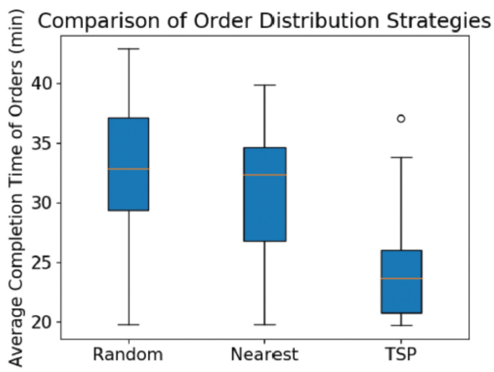
A very useful contribution to the review of this work is the study of [53] that researches the *adaptive dynamics of Online to Offline (O2) businesses*. The complexity of such systems is located in the millions of transactions that need to be processed (close to real time, by the merchants) and the challenges imposed by the varying travel conditions that influence the efficiency of the orders delivery.

The paper of [53] uses a multi-agent model that combines that behaviors of *merchants*, *couriers*, *dispatchers* and *customers* in order to model their complex dynamics. The idea is to design, simulate and then extract useful information about various delivery strategies.

Although the work focuses mostly in creating an actual platform for future use rather than extracting important academic results, there are a few points worth mentioning. Figure 5a presents the calculation of the couriers count vs. load limit for various demands while Figure 5b presents the average completion time of various order strategies.



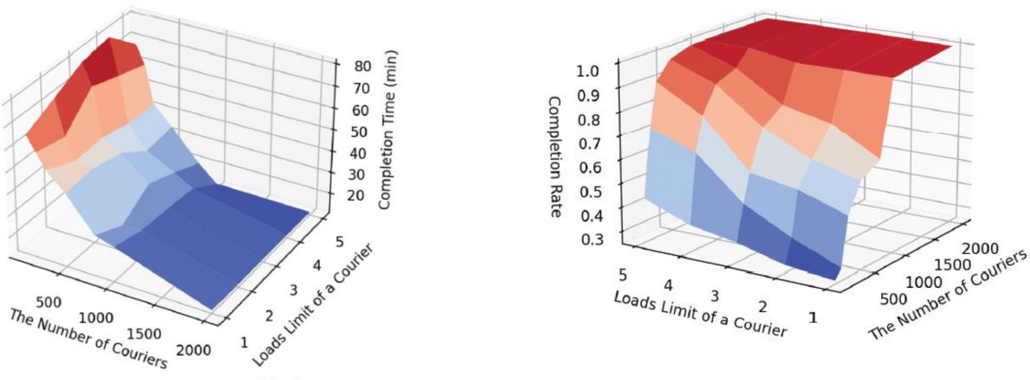

(a)




(b)

**Figure 5. a) The required courier count with respect to demand and load limit.**
**b) Average order completion time for various distribution strategies.**

The preliminary results show that a TSP-based strategy outperforms the random and near-merchant assignments. Also, they demonstrate that a larger load capacity improves rate of orders completion rather than completion time (see Figure 6).




**(a)** **(b)**

**Figure 6. a) Completion time over courier count and order limit**
**b) Completion rate over courier count and loads limit.**

When examining the problem from the human-resource view site, assuming a fixed demand, the couriers count decreases as the load capacity increases, up to a point and then the trend flattens. At the same time, a high value of demand motivates the deliverers (couriers) to improve the number of order assignment per hour.

The platform has been tested using a real road network and real order data, demonstrating the applicability of the idea of multi-agent models in (online to offline) O2O businesses, i.e. businesses which entice customers through digital media.

### 3.6.2. Decision Support System Fresh Food Supply Chain Management (Forecasting)

Another important dimension that needs to be considered in this review is the concept of **forecasting** and the available tools that can facilitate towards such estimations. This is also why the authors of [54] focus in creating a *Decision Support System* (DSS) for the sales forecasting of packaged fresh and perishable products.

The selected forecasting model family is based on the *AutoRegressive Integrated Moving Average* (with and without *Exogenous* variables), i.e. ARIMAX and ARIMA, respectively. The models focus on the impact of prices by utilizing two alternative algorithms for tuning. The DSS is parameterizing the system based on the performance criteria set by the user. Then the sales forecasting is considered a projection of the expected demand (accounting for its variability and any impact this may have to exogeneous factors) and a multi-objective algorithm is run to optimize the non-dominated orders, while taking into consideration the *freshness* and *volume* of the residual stock, the *shortage* and the *outdating expectancy*.

The performance of the designed DSS is tested by a set of real data against a benchmark. The results show that the DSS is capable to provide liable order plans, creating satisfactory performances, with minor forecasting errors and in short computational time. There are, however, configurations like the SPO with tend to provide better results, with a longer computational time, than the configurations that adopt grid search.

As regards the ideas on future research work and useful improvements, the authors of [54] state that there are many elements which can have an impact on the overall forecasting results, like market and weather conditions (plans of competitors, last minute changes on any point of the supply chain, even promotions or festivities). The structure of the DSS can include an adjustable statistical baseline, implemented to allow for contextual extensions that will intergrade fitness functions to cope (to some extent) for such uncertainties. One idea towards that end is to enrich the set of *Key Performance Indicators* (KPIs) of the model, which account for cost and quality of service, with *supply chain costs, risks*, *sustainability factors* and *customer service fluctuations*.

#### 3.6.3. Decision Support System for Collaborative Supply of Food (Food Co-ops)

One final aspect of the food delivery markets are the **food cooperatives**, which are small structures that operate in the frame of an autonomous ecosystem where **the terms of production and distributions are set by its members** (usually the local/regional supplies and consumers). The small order quantities require special logistic efforts which challenge the operations of such cooperatives. In order to create a sustainable small market in that sense one needs to consider the complexities of such a system in order to manage the collaborative logistics activities of all players involved.

The authors of [55] created, for that purpose, a DSS which aspires to simulate and optimize the system in terms of travel distances, number of vehicles and delivered food quality.

The results show that the small-scale settings will favor the collaboration of multiple food cooperatives, while the large-scale settings favor farmers (because an increased amount of orders, justifies outsourcing which favors the distant players in production). An important issue that arises from these results is that the scalability requires proper sizing estimation and a clear perception of the current status of such a system. An extra issue to take into consideration is that the delivered food quality may deteriorate when joint activities create additional loading-unloading activities.

An idea of future work is to investigate the offerings of joint storage. However, in order to encourage collaborative activities, the government needs to produce **new legal and regulative settings**. Further studies can also be conducted towards the social aspects of the matter, like the **individual will to support such activities**, the **group-dynamics in the decision-making set**, the **interdependencies of interests of various stakeholders**, etc.

# 4. Thesis statement on Systemic and Algorithmic Concerns

## 4.1. Systemic Issues

### 4.1.1. Risk Factors in Perishable Goods Transportation

Transportation happens to be an important aspect of the industrial revolution, let alone the industry of perishable foods, as it is a key ingredient in the mix of the VRP properties that constitute the nature of the pick-up and delivery market. Subsequently any precarious structural characteristics and flaws of the transportation field constitute points of weakness and potential failure for all VRP variants. The authors of [56] realized the imperativeness of researching and outlining various risk factors regarding routing issues, hoping that such a research will strengthen the respective tactics of mitigation and avoidance.

The methodology that was used is an interactive management method called ***Interpretive Structure Modeling*** (ISM) which helps the researchers to distinguish and bridge **semantical (meaningful) connections between explicit elements** which are considered as characteristics of an issue (providing methods of requesting of that elements). The ISM allows the understanding of the underlying structure which may exist in the arrangement of related components, providing an extra (ontological) path of investigation for these components. The method is called *interpretive* as it infers reasoning based on the components' inter-connecting (influence) structure, showing the formulated contextual relationships, or innate arrangement of the whole set. It is regarded a demonstrating method as its results can be depicted in a digraph.

From a literature point of view, the analysis of [56] leads to the following risk factors, enriched with a few more from the analysis based on the current review, followed by the disclaimer that this is given as an input for an extended future study:

a) Insecurity – for personnel, processes and vehicles
b) Improper food storage/holding policies/practices for products that are about to be dispatched/shipped/inspected
c) Lack or of temperature control
d) Contamination from other containers
e) Improper loading/unloading methods

f) Improper sanitation practices

g) Accident during the distribution of goods

h) Problems related to infrastructure

i) Improper design of the lunch boxes, wrappers, or transportation units

j) False usage of packing material or improper packing/placement

k) Lack of or not following a regulatory frame

l) Adoption of non-standardized conditions

These factors complement each other providing a realistic picture of the given case study. The authors stress that the biggest risk factor of them all was found to be the accidents (g). Then the lack of security (a) and the loading/unloading methods (e) come next. Finally, the contamination (d) and the infrastructure issues (h) seem to be loaded with the smaller risk.

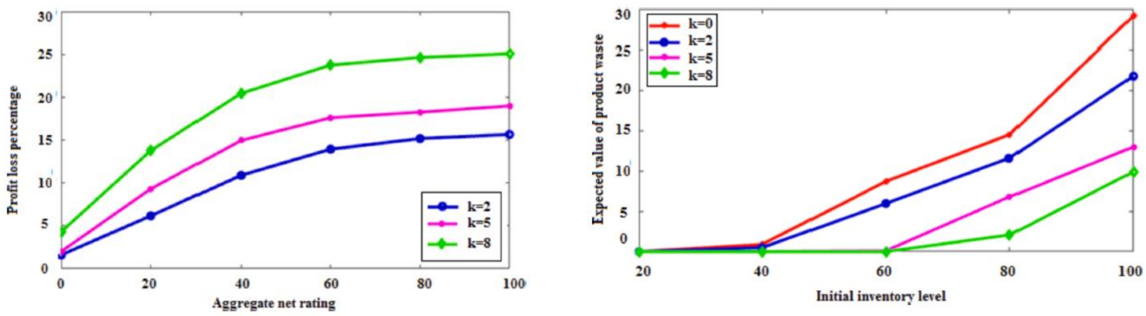
#### 4.1.2. Pricing and Inventory Control in relation to Social Learning

The commercial movement of the physical to online retailing in general, and especially during the period of Covid-19, has stimulated a similar increasing shift of a series of supporting tools of that market, like, for example, the word-of-mouth communication, to allow for consumers to proceed sharing their experiences, online. In this environment and under such transitions the authors of [57] examine the impact of **Social Learning** in the conventional practices of pricing and coordinated inventory control. The theory of Social Learning is a behavioral theory which posits that an individual's new decisions are learned/affected by observation and imitation of others decisions, through a 4-step process (***observation***, ***internalization*** – where meaning is first created, inside the observer's mind, ***imitation*** and ***feedback***).

The case examined in this paper, although this by no means restricts the application to a much wider range of societal conformities, refers the awareness about quality reduction when selling a perishable product under *Expiration DATE-Based Pricing* (EDBP). The model that was developed is analyzed on a two-period lifetime product.

The results have demonstrated that the EDBP can be promoted (for the acquisition of new customers or the strengthening bonds with the existing ones, for example) by adopting an online consumer review system. To fine-tune the outcome, the assigned manager can adjust pricing and inventory policies in relation to the review system ratings. The authors add that with the same system in place, the company can improve profit and waste management, too.

The numerical and sensitivity analysis conducted in this work, clearly present the very promising variations depending on the degree of $k$ which is the social learning parameter. As shown in Figure 7a by the evolution of the aggregate net rating of the consumers, when the social learning effects are ignored i.e. the operations management neglects adopting to the new standards, if these effects are low then this has little impact on the revenues, but if this is high then it has great impact on the revenues (subsequently the profit loss percentage). Figure 7b depicts the expected value of inventories which deteriorate by the passage of planning time (planning horizon) which does not increase by social learning intensity ( $k$ ), leading to the conclusion that social learning, as shown graphically, reduces product waste.




(a) (b)

**Figure 7. a) Profit loss percentage for not taking advantage social learning**
**b) Impact of social learning on the product wastage.**

From a managerial point of view, it is shown that the coordinated dynamic pricing and inventory control, under the exploitation of social learning effects, can not only increase the profit (revenues) but also decrease the product wastage. This, in turn, confirms the group dynamics of social learning that allows customers to infer and/or control the popularity (the common perception) of the aiming practice (here EDBP). The determination of the optimal pricing and inventory control was done using *Dynamic Programming* (due to the overlapping subproblems). The model has been confirmed to be successful to inject/embed the social learning behavior tools into the managerial policies of the firm. The negative effect on the quality issues of the EDBP were successfully counteracted by the adoption of the consumer review system. One excellent tactical move that can benefit from social learning is sacrificing the firm's policies up to the point that these can yield fruitful results in the future demands, capitalizing on the consumer's ratings. This technique resembles – and for the right reasons – the **net-politic** science theory and its applicability of the new world-order of diplomacy.

## 4.2. Political Issues

### 4.2.1. Platform Labor, Gendered and Racialized Exploitation

Some of the best contributions towards raising awareness on the discrimination matters (mainly gendered and racialized) of the sharing, on-demand, and low-income service economies, are the works of [58], [59], [60], and [61].

The most iconic openings of these works belong to [58] with the paraphrased question "***how to value anything that one cannot, and often does not want to, acknowledge***". The author of [58], Niels van Doorn, does a great work examining the distribution of vulnerabilities and opportunities related to the digitally mediated type of work, here referred to as *platform labor*.

The work is split into 4 main parts; the first one describes the 40 years of ***neoliberal socioeconomic reforms*** of our society that have shaped and placed (situated) the on-demand economy to its current state. The second one argues that such platforms are the new players of the gig-economies which use practices that further deteriorate the already stressful working conditions of the workers. This is done by a) ***falsely promising immunity*** to all clients of the platform, leaving the intermediaries (delivery agents) out of the equation, b*)* ***failing in some cases to properly enforce control over the labor force*** that maintains the governing rules of this (asymmetric) schema, and c) by ***nurturing the perception of a fungible and superfluous*** labor force. In the third part, Niels van Doorn analyses the path of history and how it reached into the present formulation of the digital economy. Finally, on the fourth part an attempt is made to address the idea of ***platform cooperation*** in relation to ethnography and to use an educated plan on how to empower the low-income workers that *are highly dependent upon the fair operation* (and high-performance) of such platforms.

There are various strategies that play an important role in immunizing the buyers of a service (both ends of the delivery process, firm and agent who receive the latter's service) and the firm that owns (licenses) its rights to the process, protecting both (the end customer and the firm) from any obligations that may be arising from commonly engaging to an employment relationship with the mediator.

One way is by **misclassifying** (through the Terms of Service, ToS) the hired personnel **as independent (sub)contractors rather than employees**. The service is quoted as a software generated product (or market in general) which is categorically distinguished in the law, allowing the firms to lawfully avoid paying for compensations, insurances, benefits etc. thus saving up to 30% in laboring costs. The firms, on the other hand, benefit from a high level of control over the worker's role without any accountability for imposing them to the constant high-performance stress that the worker has to endure in this relationship, with minimal stability and work security.

The problem begins with the **unilateral discretion** that the ToS agreement offers to the platform owner. The owner reserves the right to modifications, at any time, rendering the relation asymmetrically dependable, and since he/she needs to detract from appealing for changes, regulations, or decisions, his/her negotiating power is minimal and insecure.

One more issue relates **to the interface that collects and displays the information mostly to the platform owner**, much less to the end-users and almost none to the workers, shifting the power dynamics (for the case of delivery for perishable foods) towards the restaurants, the fleet owners, the aggregators, and the OFDA (platform) owners. A good example of skewed dynamics is the Uber drivers that need to accept an offer before they are shown the actual fare information (destination for example). This way their position in the platform weakens.

A third immunization tactic that distances the workers from receiving any negotiating power is the **optional outsourcing capability** given to any of the capital-investing role (usually the restaurants and the platform owner(s)) to hire *Customer Service Representatives* (CSRs) or additional/novel algorithmic management tools that work as legal shields between them and the service providers (here delivery agents). The phrase that best describes this was given from Tomessetti in 2016 on [59] stating by paraphrasing that "***this is done in order to dissolve authority into the disinterested medium of a software program***".

The workers need to be reclassified as employees, and the future judicial verdicts to include obligatory terms that enforce their negotiating positions under collective agreements. However, even if all of the above challenges are covered, there are more issues that need to be addressed, as the platforms exercise asymmetry of control through more means. For example, the on-demand platforms are designed to monitor all the information of the service workers that are placed under the same platform umbrella, and the service workers **get only the competitive feedback** with comparisons of their performance to other workers, **or overall rankings** in order to create a sense of relationality, prohibiting any other communication between the workers.

The customer review and rating system can be another mean of control, as the collective perception **turns into a decentralized, audit culture** which can be externally controlled in the same manner that is done by the reality TV shows, where the selective promotion or marketing of specific behaviors can be collectively interpreted as the new standards or metrics. In both cases the shift of collective perception leads to a shift of what is the new setpoint of optimality or minimum performance. And the 'best' part (for the platform owners) is that this can be achieved with no consequences since human perception evades the mind stress and the memory required for a backward traceability level that is accompanied by a high-level of confidence for the source of the problem.

Another concept, that has been pioneered by Uber, is the **data-driven techniques** that create incentives to move drivers to high-demand areas at certain times, which soon turned into a controversial practice. These surges of high demand create uncertainty among the drivers who cannot negotiate on whether this an economically rational (and fair) decision for all the parties involved, as they seem to pay the extra price when responding to such algorithmic prompts. This technique of logical management is exercised in a pervasive manner and although they create '***instant task gratification***' perks for some cases and for some roles, this authoritarian style with negligence to the service provider increases the on-demand labor contingency.

On the same note, these platforms use internal **enrollment techniques** with incentives for new hires, managing the **turnover** so that there is always surplus of population to cover the demand, keeping the underemployed workers on a level of **fungibility** and **superfluity** that is managed by specialized digital architectures [60]. This well calculated depreciation ***renders the workforce an easily substitutable, abundant commodity through a central strategy that valorizes the tension of expendability and necessity by controlling hiring rates***, thus the geographical expansion of the platform, gradually pushing for massive growth only when the wages attribution makes economic sense with the aforementioned terms. As Chayka mentioned in 2015 in [61], the investment into a model that will ensure **equitable labor conditions does not lay side by side with the intentions of high scalability and profitability** which are the two main criteria for venture capital offerings.

The work of [58] proceeds by referencing a number of researchers around the deepest racial biases regarding the experience of value, visibility and violence in the work force of gig economies. The example being used in 'Hello Alfred', 'Managed by Q' and 'Handy', all commercial firms that seem to focus in doing what is required to **deface and dehumanize the offered service** (like cleaning, making chores and anything that may be considered as degrading in the 'post domestic' world fantasy of some clients), to escape from any intimate human interaction between the served and the servant. These firms are mentioned in the work of [58] as implicitly yet deliberately post-racial and gender-neutral constructs that promote such services ***by removing anything that reminds to the customers what has been historically degrading their offerings*** to be of so low value - ironically promoting them as inclusive and equal opportunity companies.

The key conclusion of [58] is that inequality (producing the lack of fairness) "***is a feature rather than a bug***". The platforms seem to be constructed in ways that embed initiatives which exercise what is called *flexible market optimization* with conditions that are creating beneficial settings and profits from the (indirect) subordination of low-income workers. Ironically enough, these lines are written in August 2022, just a few days after Uber was found to be guilty, once again, receiving numerous accusations about politically driving high-profile public officials in France (like Emmanuel Macron in 2016) to create beneficial policy-making for its lobbying operations. The Guardian mentioned a number of leaked files in July 10$^{th}$, 2022. The real ethical and legal issues are yet to be settled, and only history will tell the extent of this corruptive attempts.

One hopeful and quite ambitious initiative that may efficiently carry the burden of constantly re-examining the processes of corporate self-regulation (and to meet the appropriate levels of social justice) is the **Good Work Code**. This establishment was constituted in 2015 by the National Domestic Workers Alliance (NDWA) in USA when it became apparent that the domestic workforce is moving online (i.e. the on-demand platforms).

The code has 8 important values

- Safety
- a Livable Wage
- Stability & Flexibility
- Shared Prosperity
- Support & Connection
- Growth & Development
- Transparency
- Inclusion & Input

and aims to healthy market self-regulation while pushing for regulatory and legislation actions that advance social care and justice for workers. Also, it operates as an innovation hub that promotes strategies that aspire to improve the quality of workers, called 'Fair Care Labs'. **Hubs** like this one are very valuable since most of the debates on how is technology reshaping the contractual terms and the lives of the low-income workers in general, happens in conferences and institutions, from academics, business consultants and/or policy experts, speaking for the life-struggling topics **of the gig workers who lack appropriate representation in general**, let alone when discussing on platform-mediated labor issues. There is a lot to be learned not just by the context but also by the tone of the voices from the people that want to share their daily experiences, aspirations, anxieties and perspectives – and this can be done by just one microphone and a direct representative from the workers, in each and every one of such meetings.

As Niels van Doorn puts it, in a materialistic (pragmatic) approach, we will all need to experiment with novel platform architectures that are made to support cooperational schemes, aligned to a social justice that tries to acknowledge the need, but not conform to the opportunistic logic, of capital and market. The **platform cooperativism**, as Niels explains, will require to be articulated by the experience of credible public institutions in order to create a unified legitimate entity that will cover its sustainability and scalability.

#### 4.2.2. Discrimination in Sharing (Gig, O2O or On-Demand) Economies

The work of [62] that was published to the Applied Economics of the American Economic Journal presents the findings of an investigation conducted over a field experiment on racial discrimination, adding to the numerous societal and academic efforts to reduce discrimination incidents on the workplace environment. The experiment was focused on Airbnb and it was found that candidates with African-American names are 16% more likely to face some kind of excuse or change of occupational terms when compared to identical cases with names that resemble white ethnicities. This was a uniform outcome for discrimination, existent among all sizes of properties, and pronounced mostly to hosts that had never served an African-American guest.

The work makes one step closer to quantifying the **cost of discrimination**, by suggesting that, in terms of net revenue, this is the listing penalty due to the hosts discriminatory actions times the probability of such an occurrence, i.e. leaving the listing empty. Excluding all other unobserved costs and benefits (like providing positive feedback if they were accepted, which draws future guests and improves listings) the median cost was calculated to be from $65 to $100 for each case being discriminated when the median price of the apartment(s) is from $163 to $295. Although it is evident that the numbers are depending on a series of factors, like societal norms, geographical area, types of business, types of rental, season of the year etc., it is still enough to provide a primary evidence on the hypothesis that discrimination comes with a high cost for the host, let alone the potential guest.

#### 4.2.3. Multisided Fairness, FairRec and the Asymmetrical Transaction Nature

This paragraph can be regarded as one of the most relating to the conceptual sense of fairness of this chapter (and of this thesis), since its sources ([63], [64] and [65]) seem to interconnect the **existential reasoning behind the manifestations of its systemic, political, algorithmic and social challenges**. The paragraph is split into 3 main sections, each one describing one aspect of the nature of fairness as it is materialized in the OFDAs platforms.

The authors of [63] examine the challenge of creating a fair personalized recommendation system (a PRS, called FairRec) in a two-sided online environment, i.e. one that is based on two main distinct roles, the producers (servers) and the customers (clients). It is well established that the conventional model is focusing on enhancing customer satisfaction by customizing the served experience according to the personalized preferences of these individuals (the clients). This client-centric approach creates an unfair distribution of worth and accountability which impacts the clients' well-being. Since a server-centric approach would lead to the opposite effect, the authors of [63] decided to follow an approach which involves a novel mapping of the PRS to a constrained version of indivisible goods. The algorithm guarantees MaxiMin Share (MMS) of worth (exposure) for the majority of producers (servers) and Envy-Free up to 1 item (EF1) fairness for all customers (clients).

The results which were generated from simulations that were fed with real-world datasets, confirm that FairRec can be quite effective in balancing and ensuring the two-sided fairness, with a **minimum loss on the overall recommendation worth** (quality exposure). The exposure inequalities tend to create monopolistic trends for the servers leading to some of them struggling and switching to other platforms, which subsequently translates to an overall quality service reduction for the clients. Thus, although inequalities can be a driver for a free market, great inequalities that are unfair and cannot be justified and treated will only bring negative effects for all.

According to the work of [63], as people that depend on two-sided recommendation platforms are gradually entering the OFDA marketplace, more and more of these platforms introduce fair play activities for all stakeholder, due to: (i) legal obligation (like Uber and Lyft), (ii) voluntary commitment or social responsibility (like LinkedIn or Airbnb as it was described in 4.2.1 and 4.2.2) and (iii) business model/strategic decision (like Airbnb did with its guarantees for minimum revenues).

After a brief survey, the authors turned the problem towards two directions, the one relating to **fairness about the multi-stakeholder platforms** and the other to the **fair allocation of worth** (goods, etc.). The first part has been already mentioned and will be even more investigated in the paragraphs to follow. The second part is known as the *cake-cutting* problem and it belongs to the computational challenges of *social choice theory*. The most notable notions of such fairness relate to envy-freeness (EF) and proportional fair share (PFS). There is a rich literature on the subject of fair allocations which has been well investigated by the work of [63] as seen by their model formulation regarding the relevance of products, the customer utility, the producer exposure and the final experimental evaluation. The choice of EF1 over the guarantees of MMS has been well documented.

The experiments show that the increment of **minimum exposure guarantee** creates lower producer exposure inequality, but it can cause higher losses of worth (exposure) for the popularly established producers (as expected). Finally, higher producer exposure can (if not properly regulated) negatively affect customer utility. In conclusion, the experiments have shown that FairRec manages to establish the anticipated guarantees and produces empirical outcomes that serve as adequate evidence for the applicability of the tool in fair recommendation challenges. As to the future work, Robin Burke aims to tackle the ***position bias*** by studying the ***attention models*** that lead clients to adopt a myopic behavior with their attention being monopolized by the top-ranked products.

The work of [64] is also investigating the issue of fairness to recommendation. More specifically, the author shows that, depending on the context, fairness can be regarded a multisided merit, where a fair service to be server equally to all is quite challenging. The author (Robin Burke) presents a taxonomy of such systems and discuss on the use of fair types of architectures. In this context, it is important to understand that the recommender systems aim to facilitate and increase transactions in a personalized manner. **Fairness deviates only in the sense that it may serve individualistic interests**, which, when applied only to a specific group of people they can be transformed into privileges.

As per the ***personalization***, in order to achieve a purely personalized approach from an automated system, an expert will need to continuously identify the biases that will claim global preference ranking and the specificity extent (classification granularity) of the identified items. For example, it may turn out that male users are seeking on high-paying jobs but some users may prefer other perks, like flexible hours. Thus, a moderator will need to step in to control the algorithm in order to redefine its sensitiveness in the salary distribution domain, per that new dimension which may skew the perception of fairness for such a class.

In a ***multi-stakeholder*** recommender tool, the users whose preferences participate into the set of variables to be optimized, are from more than one group, meaning, for example that they can be both servers (producers) and consumers (clients), as in 4.2.1, or job seekers and job providers as in the last example. Such a tool requires to find a solution that weights the considerations of both groups, which means that it needs to cover multiple goals at once rendering a user-centric approach inadequate. Examples of such platforms are LinkedIn, Etsy, Kiva.org, etc. Tools like these use multiple stakeholder utilities, that are domain specific, and which, may even require frequent adjustments.

Regarding the multisided fairness, there are three different types that relate to the server-client / producer-consumer groups. These are C-fairness (for consumers), P-fairness (for providers) and CP-fairness (for both). The C-fairness is taking into account the protected group of consumers, the P-fairness the same for the providers and the CP considers the case for both.

For the **C-fairness** case one could create a special mapping from each protected member to a prototype space which could include latent factors that would be extracted from the review/rating data. If this is engineered to have some statistical connection that provides positive feedback or leads to a beneficial impact to the providers relative to the protected class then this would ensure a bounded loss with respect to the accuracy of the ranking of the users.

The **P-fairness** includes some extra dimensions that need to be considered, since their existence is important for the *market diversity* (as already discussed) and at the same time it avoids *monopolistic domination*. Although such fairness is not forced by law it is still considered an important property of such fair-aware systems. An important differentiation of the two protected groups (providers over consumers) is that the providers are passive, in the sense that they wait and no not seek or wonder as the consumer do, scouting for opportunities. The opportunity for providers may come only rarely and this need to be acknowledged as such. Some of the research in the area of diversity-aware recommendation aims to maintain accuracy while remaining diverse-friendly. Such methods can be repurposed to optimize for diverse recommendation in the sense of the passive over active asymmetry, if and when required. The issue of injecting fairness into the matter comes over an important literal distinction that is made between the *list-diversity* vs. *catalog-coverage* methods, where the first differs against the second on their focus (individualistic vs. collective). In other words, the list-diversity can lead to the promotion of diverse items to every member but it will not provide a fair outcome when considering all the providers. In order to achieve both goals, a more dynamic model is required. An exemplary implementation is the tool of on-line bidding facilitating the advertisement displays where a fixed and limited amount of money is spread across the users by many competitive marketers. The algorithm that balances such a budget breakdown is called BALANCE.

The **CP-fairness** can be found in reciprocal recommendation or in any schema where both C and P entities belong to protected groups. An example of such a case can be a recommended for the case of 4.2.1, where a rental property provider (landlord) needs to engage to a lease with a minority applicant which, for this example, belongs to the protected class, while at the same time, the tool wishes to regard minority landlords as a protected class also, ensuring high quality guests at a rate similar to the one of white landlords. The two statements, are expressed so that they lead to decoupled solutions, which means that only a C-fair recommendation ranking will be forwarded on the mechanism that checks for P-fairness.

Robin Burke feels that this CP-fairness approach most certainly works, however it is important to find out how will the overall system solution and the individual outcomes of each stakeholder (for C-fairness and P-fairness alone) be affected when these solutions are combined. Also, as to the limitations of this work, it is mentioned that the main challenge lays in the *domain specificity* which renders the utilities of each stakeholder class highly dependent on the actual data that define/characterize the specific business model. Therefore, it is very hard to generalize across various recommendation scenarios unless appropriate data are available.

An important case study that offers an exploration to the algorithms of OFDAs that govern the respective laboring in China (through Baidu, Eleme, and Meituan), is given in [65]. The author, Ping Sun, examines the sense that is made out of the parameters of *temporality*, *gamification,* and *affect* (emotional labor) by the applied algorithms. **The study shows that the workers are not just passive conformists controlled by a digital entity but they create their own rules, forming 'organic' algorithms, and through this mix they manage what does and does not fit as a rightful set of conduct**. The results suggest that these algorithms (which tend to be expressed as 'collective human practices' as Seaver in [66] put it in 2017) need to be constantly re-formed and to constantly adapt and learn from what is beneficial to human behavioral economy, but **not just be sensing the numbers' feedback, but actually, the actual nomenclature and rhetorical positioning of the workforce**, by looking deeper into their choices for proper/handy adjustment to the layer of reality as they face it, and by listening to the real humans themselves.

Through a set of questions, Ping Sun explored the politics of the platform and the ways that the workers are experiencing the algorithmic dimensions already mentioned. The findings show that the 'entrepreneurial individuals' are more strictly managed. Also, the algorithms that were value-free and impartial are enhancing capitalism and prioritize the interests of the owners and the customers. As to the leisure time of the workers, in any ideology that serves performance metrics, same to what is done in the physical world, the essence of labor in the digital world of such algorithms is also undermined. The worker's leisure is lost as part of the granted rights of the workforce.

As Ping Sun concludes, there are **asymmetrical power structures** which are the results of social inequality projections, so deep-seated at several levels of life expression, existing long before, and having no relation to, programming and computer algorithms. The authors of [66] speak about a 'methodological genocide' since these simplistic and out-of-ordinary human behavior algorithms disregard emotions, context, meanings, history, specificity, culture, human relations and societal structure. The *ethnographical* study regards algorithms as embedded entities in a multi-layered sociotechnical operation.

There is an abstract conceptualized argument to some that algorithms can become better fitted to the human ways of life, which subsequently leaves room for hoping that such an existing gap can be the reason of the human struggles against the machines. Although, it is true that better fitted algorithm designs, that will be closer to the human experiences and practice, will always help, there is still a lot to be said and researched, regarding the deliberate formation of such algorithms that just neglects the struggles of the workforce and the impact of corporate greed to the fabric of society. In the advent of the 4$^{th}$ version of the Generative Pre-Trained Transformer (GPT), which is an ongoing project of OpenAI (a non-profit research institute), the gap between what is intended and what is implemented will be further reduced. This means that corporate environments will soon be closer to creating better tools that 'understand', imitate and express human nature in a much better sense. GPT-4 inherits its virtue as a meta-learner from its large context window and sophisticated design that takes it a step closer to the reasoning of human brain. This means that the programming interface for the creation of such algorithms will surpass the language barrier and there will be much more open space to explore, validate, and most probably confirm, the critics of Ping Sun.

#### 4.2.4. Mitigating Traffic Risk – Corporate Social Responsibility (CSR)

The work of [67] investigates the traffic risk due to the dangerous driving of the stressed food delivery agents and tries to reduce it using spot check and information sharing. The model of this work inputs the consumer's demand using statistical analysis and bases the modeling of the problem as a **Stackelberg** game between the OFDA and the government. The Stackelberg model of leadership in used in economics, assuming that the leader moves first and then the firms follow in a sequential manner. This is based on the research of '*Market Structure and Equilibrium*', which was published in 1934 by Heinrich Freiherr von Stackelberg.

The main findings of this work are based on numerical studies which were conducted to check the way that the government's regulation strategy affects the platform's CSR implementation and subsequently the utility of the two. The main scenarios that were considered are a) the social concern change for the traffic risk, b) the effect of the publicity intensity for the traffic risk and c) the stakeholder's utility. It was shown that both the government and the platform can benefit from publicity. The government uses spot check policy to regulate the platform fines and the publicity policy of traffic risk, in an indirect way. The point is that despite that the spot checks reduce the traffic-risk, they also create more fines for the late platform orders. At the same time, the numerical results show reduction on the platform fining by the traffic risk publicity.

So, in order to increase the social welfare, the authors **propose the regulating effort on spot check and publicity** (raising public awareness), when a market size exceeds a specific volume. If the market has a smaller size that a setpoint then the optimal strategy will be somewhere between the two, alternatively adopting each policy for a variable amount of time, depending on the received feedback, until the rates for each are settled.

### 4.3. Contingency Issues (Covid-19 challenges)

#### 4.3.1. Riders of the Storm – Platform Precarity

The pandemic of Covid-19 which had impacted the global economy on so many levels, has also been one of the main factors (along with the lack of proper counter-measures) for the deterioration of the labor conditions of China's food delivery agents. The work of [68] makes 52 in-depth interviews to examine the power of this effect. The main struggles are the increased risks of **physical accidents**, the inflamed **societal racism** and the **livelihood crisis**. The issue is enhanced by the coalitions between the food delivery aggregators (platforms) and the Chinese states, which subsequently increase the work load, the unpaid part of the labor, the non-compensated extra time and the investments in capital assets instead of the social welfare.

The four-fold struggles of the delivery agents are based on the following points: a) the interaction between the supplier and the end-user are configured (governed) by a digital entity, b) the optimization is based on various **underpaid, monotonous micro tasks** c) the **contractual status is unfair** as it is based on workers willing to serve as free-lancers (independent contractors) limiting the liability of the employer and his/her obligations to rightfully and lawfully acknowledge the work-related welfare entitlements to them and d) **the performance is evaluated by strict terms without considering or compensating for the peculiarities of each worker** who is obliged to provide a standardized service (when not all workers have equal share to the emerging opportunities or do not need to pay the same amount of effort to cover an order).

During the pandemic the delivery agents were treat as heroes in the media but like slaves in reality. The discrimination and fear that they were carriers of the virus was evident. The alienation that followed fired up racism related to the citizenship. They also got blocked or had to wait for order confirmations while waiting in building entrances. Additionally, they had to be regularly tested, to buy hygiene products themselves including disinfectants, masks and other gear for the (motor)bicycle, all paid by themselves. There was no compensation by the state for the extra work hours, or the penalties for the cases that orders had to be delivered late and at areas of high risk. At the same time, they were more exposed to the virus that most of the citizens and had to struggle for the cases that the increased policing was making their work harder, without reducing their vulnerabilities. Many of the workers just couldn't afford all the cost that was adding up as a burden on their shoulders that no constitution was willing to carry.

Unfortunately, although the algorithmic management would be able to easily compensate for all these issues **by relaxing the performance requirements and the ratings impact**, it became a big part of the problem, with the second being the inhumane approach of the Chinese states. The algorithmic mismanagement and contingency planning at times of crisis will be further discussed on paragraph 4.4 that follows.

### 4.3.2. Last Mile Challenge from the rider's perspective

In continuation to the previous paragraph, this one focuses on the work of [4] which examines (in the context of developing countries) the last mile (LM) challenges from the perspective of the delivery agents, during the Covid-19 pandemic. The two main questions are a) what is the nature of the LM issues during disruptions and b) what improvements can be applied by the ODFD. Both of these questions have answers that can benefit all stakeholders especially if these are processed with the *Grounded Theory Methodology* (GTM) which is considering *dynamic human behavior*, *human interaction*, and is best used in challenging social processes.

In total there were 38 riders interviewed through a GTM process of 15 steps, which were classified as round-one interviews, open coding, axial coding, round-two interviews, and selective coding, in a waterfall scheme with each stage moving backward iterations. The results of the study contextualized the main characteristics to seek and grasp explanations for the issues that the riders were facing.

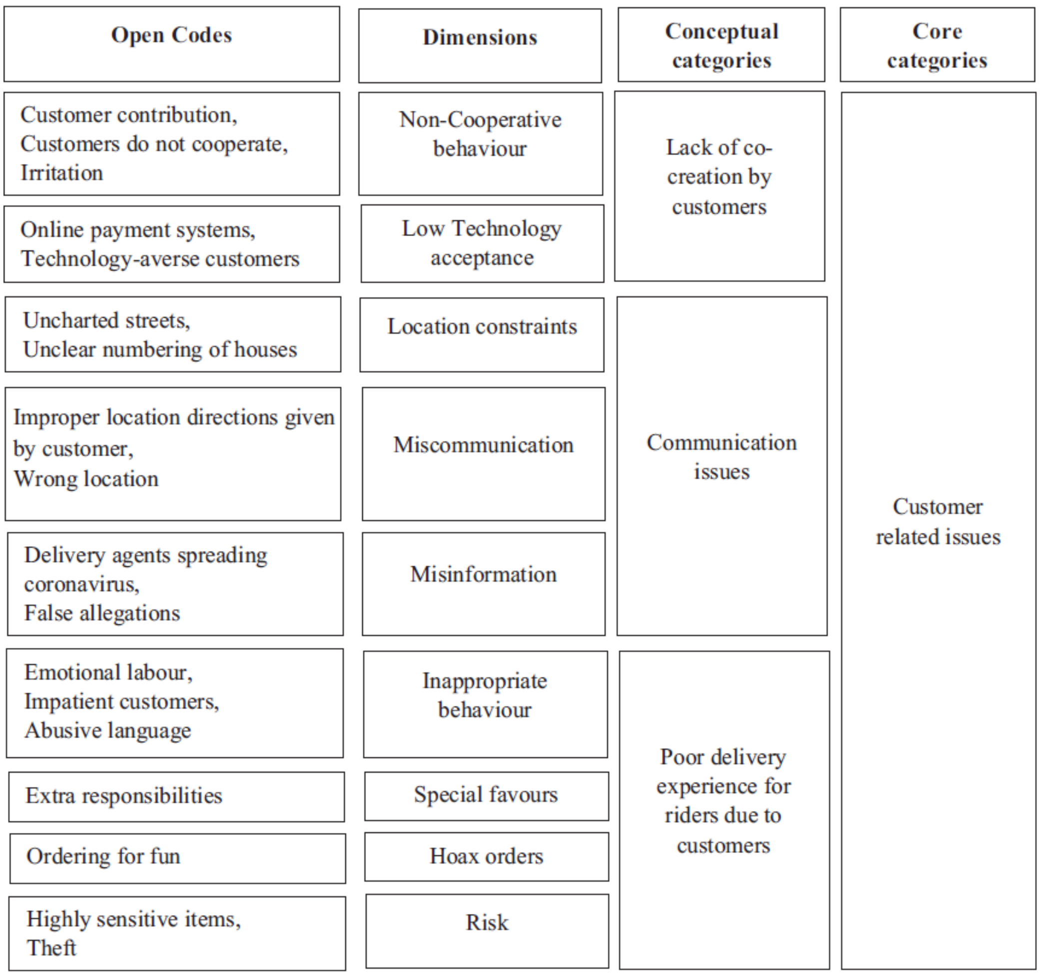



**Figure 8. Customer-related Issues**

The coding led to 4 core categories, 10 conceptual ones and 39 dimensions. The 4 categories are about *Technological*, *Customer-related*, *Organizational* and *Operational* Issues. Figures 8 to 11 that follow summarize the results.

| Open Codes | Dimensions | Conceptual categories | Core categories |
|---|---|---|---|
| Misleading, Perception of inaccurate data representation | Negative perception | Organisational ethics | Organisational issues |
| | Negligent behaviour | | |
| Reduced earnings | Fluctuating business model | Organisational policy issues | |
| Third party competition | Cannibalization | | |
| Hiring local managers | Employing locally | | |
| High importance to customers | High customer-orientation | | |
| Low demand of orders | Order variability | | |
| More labour, less jobs | Supply demand equilibrium | | |

**Figure 9. Organizational Issues**

| Open Codes | Dimensions | Conceptual categories | Core categories |
|---|---|---|---|
| Frequent charging of phone | Device life cycle | Device issues | Technological issues |
| Reduced life of device | | | |
| High usage of device | Device maintenance | | |
| Mobile phone issues | | | |
| Spending on device damage repair | | | |
| Difficulty in using device | Ease of use | | |
| Location not pinned correctly | Inaccurate location | Navigation issues | |
| Improper phone signal | Network coverage | | |
| Lack of proper directions | | | |

**Figure 10. Technological Issues**

| Open Codes | Dimensions | Conceptual categories | Core categories |
|---|---|---|---|
| Low earnings in long-distance orders | Distribution cost | Cost | Operational issues |
| Cancellation of orders, Penalty | Failure cost | | |
| Payment collection, Vehicle parking | Fulfilment cost | | |
| Frequent buying of device, Low life of vehicle | High investment | | |
| Added cost of sanitizer, Cost of maintaining hygiene, High usage of vehicle, Increased cost, need for maintaining hygiene, Vehicle maintenance | Maintenance cost | | |
| High risk of damage, Item handling issues, Rule breaking | Non-conformance cost | | |
| More orders, Waste of productive time | Opportunity cost | | |
| Fake orders, Processing for cancelled order | Processing cost | | |
| Delay due to multiple orders, Waiting at restaurant | Waiting cost | | |
| Penalty/Payment cut, Reduced pay | Compensation | Poor Quality of Work Life | |
| Long term effect on health, Inadequate focus on hygiene | Occupational health | | |
| Harsh weather, Job related risks, Lack of empathy towards delivery agents, Lack of employee respect, Lack of support from employer, managing by intimidation, necessitated regular sanitizing, Negative behaviour, Risk of COVID19, Unsafe working conditions | Working environment | | |
| Stressful situations, Fear | Ergonomics | | |
| Abusive behaviour by restaurant staff, dedicated towards work, Demoralisation, Demotivating factors, Disadvantage of long-distance orders, Drudgery of arranging change, Fear of contracting COVID19, Helplessness, hurt self-esteem, Inappropriate requests, Inefficient processing, Lack of employee respect, Negative attitude of employer, Negative attitude towards employer, no job security, Reduced incentives, Risk of COVID19, Shame, Terms not fulfilled, Uncertain earnings, Variation in area of work | Motivation | | |
| Lower earnings, Process inefficiency, Remote places, short distance deliveries are faster, long distance delivery is time-consuming,Unnecessary return to original location, Waste of time | Optimisation | Optimisation in Service Design | |
| Stacking of orders, waiting for customer order | Scheduling | | |
| Fluctuating income, uncertainty in successful delivery | Uncertainty | | |

**Figure 11. Operational Issues**

Figure 12 presents **the logic construct that serves as a conceptual framework** used for gathering all the mitigating actions for the various issues that the riders face, in one simple to visualize graph.

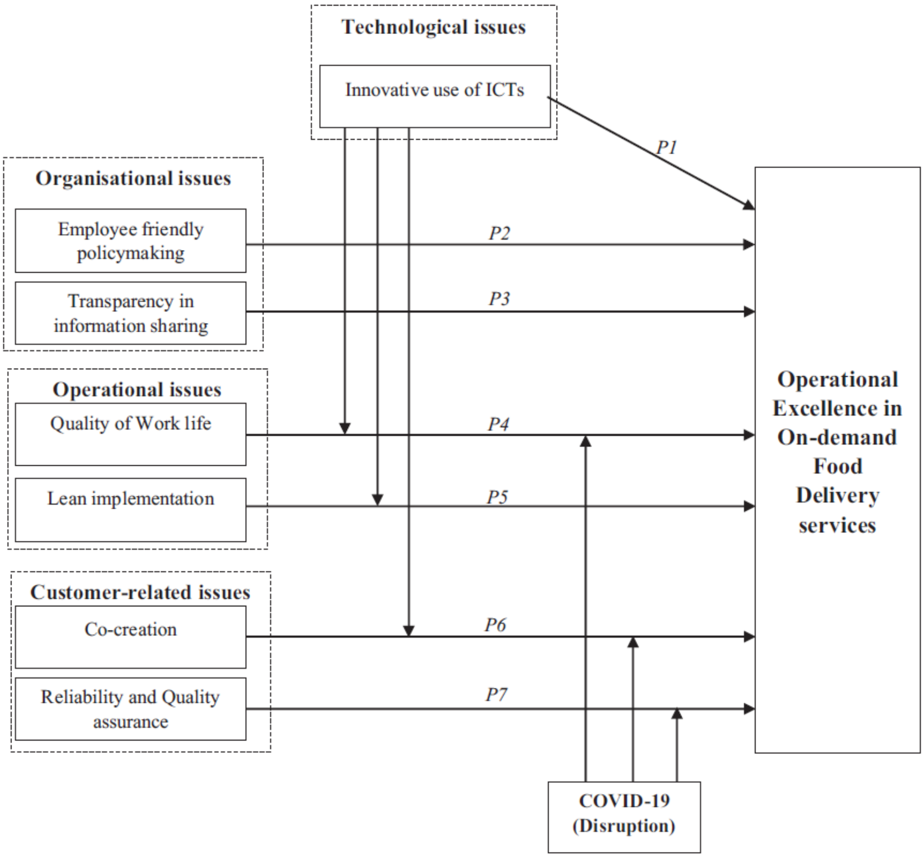



**Figure 12. The conceptual framework which aims towards operational excellence of ODFD firms.**

**P1** suggests that optimizing the use of Information Communication Technologies (ICTs) can allow for operational excellence in ODFDs **through process innovation**. For example, a periodical communication only for the location of the order and the (expected) time of delivery could allow for a service of similar quality but lower cost.

**P2** suggests the use of **employee-friendly policymaking** by proper engagement into the respective leadership tactics. This includes actively supporting the workers with fixed and standardized payouts, time shifts, work areas, order quantities, bundles, etc. which can improve the morale to a great extent.

**P3** guarantees that the information to be shared with the riders will be **transparent, aligned with the strategic interests of the ODFD firms** and will be frequent and inclusive for all riders. For example, the order allocation data and the incentive policies of the firm can reduce any accumulated confusion and mistrust. Among the data that can increase transparency and bring a sense of inclusion, are the firm positions on salary structures, ownership options, profit sharing, etc.

**P4** refers to the **work/life balance** which improves the involvement of workers (and subsequently) the firm's excellence of operations. A disruption on the one side (lie Covid-19 and a better, more humane approach that is assisted by communication technology may affect, negatively or positively, the quality of the relations, respectively.

**P5** suggests the implementation of **lean management tactics** which can minimize waiting times, over processing orders, spoilage, food defects and many other types of waste and penalties which cost to the ODFD. One way of enhancing the operations by lean tactics is for example by selecting similar, safe and well-known delivery paths and/or delivery schedules. This can be facilitated by novel ICTs, too.

One more area where the ICTs can enhance the experience and satisfaction of both the employee and the customer, is in **co-creation incentives**. **P6** promotes this idea as the **involvement of the customers** (into providing good directions, into ensuring that the packages can be collected and that there is access in the buildings, into proceeding to online payments to reduce the need to check for change etc.) goes a long way to the accumulated trouble of the employee. Also, it is a noble action paid forward to the next customer, ensuring a faster and better service and this, in time, will be received by someone else.

Lastly, since many riders reiterated that many food consumers were skeptical about the hygiene of the agents and the safety over the practices that were followed by the ODFD firms, which in turn influenced the ordering rates and behavior, **P7** suggests running initiatives like **special educational campaigns or advertisements** which would reassure the majority about the implemented standards. This would subsequently facilitate performance of ODFD firms' operations.

The authors believe that it would be very beneficial for future studies to extend this work by examining the response of riders from other geographic areas to enhance generality. Also, it would be useful to focus on other stakeholders of the ODFD ecosystem and even combine the results in order to understand which challenges can be achieved under a few common goals. Finally, it would be very beneficial if a study could shed more light into practices that would enhance the lean management of the ODFDs in the future.

### 4.3.3. Impact of a pandemic in the food supply chain

The pandemic of Covid-19 caused disruptions in many supply chains which crippled the economy by suspending many manufacturing activities and challenging most of the logistic activities in a global scale. The study of [69] investigates ways to develop, through three different contingency plans, a resilient food supply chain that will be able to match the uncertainties of supply and demand in times of crisis. For this reason, the authors of [69] create a model of a *Public Distribution System* (PDS) and examine what counter-measures can help balance the logistic actions (supporting tools in the decisions of rerouting vehicles) through simulations of scenarios where the infection and recovery growth change in time.

In the recent years many researchers have presented models that provide useful insights on **how to conduct policies that will tackle the spread of a pandemic**. The authors of [70] consider 3 scenarios where they examine the citizens' reactions and the government's counter-actions like self-quarantine, hospitalization, and movement restriction. The authors of [71] investigated the inventory of an important supporting device (a ventilator) during the Covid-19 pandemic. The work of [72] considers the logistic issues (using MIP) for minimizing deaths and infections by Ebola Virus in West Africa, with the given budget. Similarly, the authors of [73] (using MINLP) model the spreading patterns of Swine flu (H1N1) in China, under a bounded budget per individual.

As to the emerging technologies and methods that are dedicated to strengthening the balance of the supply chains and the economic impact of disruptions, the literature study found many contributions, among which the most related are a) the work of [74] where the authors establish **smart-contract tools for logistic aggregators**, b) the work of [75] which studies the **trade-offs between lead time and event driven costs**, c) the work of [76] that analyses the **strategic challenges and logistic planning** required for facing the impacts of avian influenza on chip manufacturing labs/firms, using a dynamic model and d) the work of [77] which examines ways to **meet the societal demands** (in food, logistic services and communication) **through a game-theory model**.

The work of [69] uses the graph of Figure 13 to distinguish the classes of needs and the sequence of tactical management, based in the relative importance of specific actions and constraining priorities. For example, primarily comes the utilization of crucial resources, like raw materials, personnel and active logistics. This includes medicines, food, clean water, diagnostics equipment, clinics, and Personal Protective Equipment (PPE). The essential sectors like agriculture, aviation, healthcare, railway, and Fast-Moving Consumer Goods (FMCG) come next as these will fulfill the primary reserves when needed.

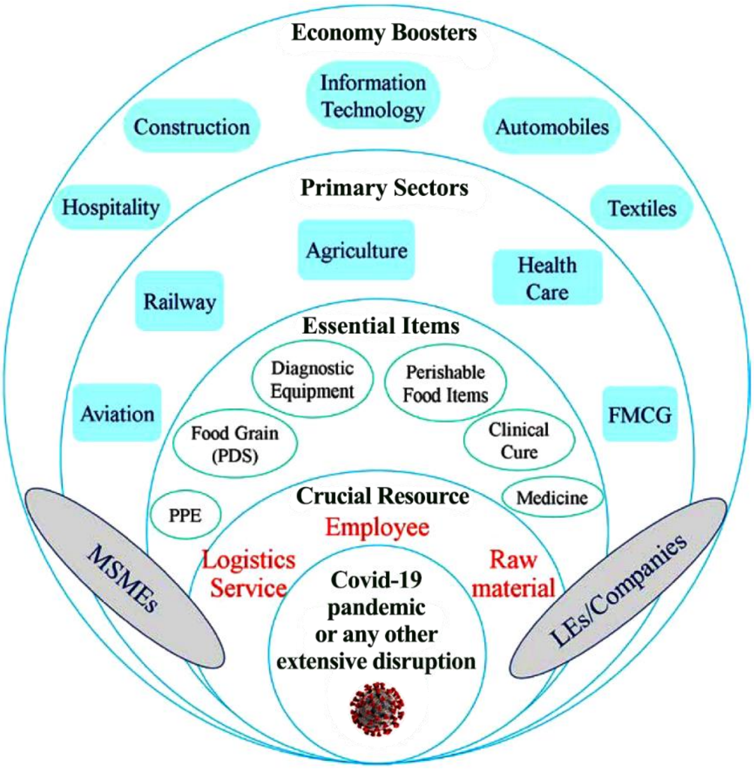



**Figure 13. Sector-wise prioritization and sequential relation of economic activities.**

It can be well established that the distribution system (especially for medical equipment and healthcare) requires **strategic optimization** at times when the supply chain needs to function in multiple speeds. In order to expedite bureaucratic burdens, the first step is to enable independent authorities and minimize the single government-owned agencies that create bottlenecks in the **optimal utilization of purchasing power**. This means that the capital liquidation needs to be high and come from multiple sources, as per the instructions of the World Health Organization (WHO) to guarantee proper coordination and minimal wastage.

As to the LM delivery, the work of [69] recommends the utilization of drones which will be used in the highly infected regions only, in order to maintain the measures regarding social distancing while reducing the times needed to fulfill demand. The same applies to the food supplies that are regarded as emergency supplies. These usually are wheat, lentils (grains in general), rice, sugar, salt, oil and in extreme cases clean water or water in general. The results showed for these cases the synchronized delivery system for trucks and drones managed to minimize the total cost and *Expected Lead Time* (ELT) of deliveries, in all the examined scenarios. Depending on the scenario the ELT was improved by 4 % to 41 %, and profits (avoided costs) from 13.3 % to 16.7 %.

## 4.4. Algorithmic Issues

### 4.4.1. Algorithmic Control and Constraints on Workers

A very extended and well-presented sociological research has been conducted by the authors of [78] who have drawn a series of 55 in-depth interviews with personnel working on ODFDs accompanied with a survey consisted of 955 food delivery agents. This research analyzes which platforms (aggregators) of the food delivery industry impose controlling behavior over the delivery agents and to what extent. The researchers have succeeded in shedding light on the level of constraints (on schedules and activities) that the agents' freedom is imposed onto, and have found that Instacart, the largest grocery ODFD platform, is the stringent one. Instacart seems to be exerting an authoritative type of control called "**algorithmic despotism**" over the workers' activities and schedule/duration. The work of [78] opens a concluding discussion on the various implications that can emerge from the algorithmic control spectrum and how these may shape the condition of the future workforce.

The authors present a **highly raised awareness** on the true meaning that the new-age transition to a promised **"flexible"** employment and its respective work arrangements, really mean. They argue that the loose contractual agreements like the part-time employment, the promise of planning autonomy, work/life balance etc., is seemingly luring. It preaches independence, it seems to allow for novel and multiple pursuits and that it collectively broadens the fields of solidarity. In reality this soon turns out to be an illusory trap for most, as the employee, who now is called an "independent contractor" / "entrepreneur" / "free-lancer", **needs to absorb the market risks and the uncertainties that used to be the responsibility of the employer**, without the guarantees of a safe health insurance or retirement plan. As Marx had **criticized the "free laborer" is free of every necessity that allows for the realization of the power that results from his/her labor**. The scholars are theorizing that the algorithmic management enables the

**strategic use of information and computational asymmetry,** which is actually the synthesizing of new old tricks into innovative management tools. The workers of the digitally enhanced world are now being monitored by personal ratings and performance platform metrics and controlled through **subliminal behavioral nudges** based on active perks and **dynamic price surges**. The activists of the field are keenly aware that the game is still the same but nowadays it lays on more sophisticated foundations that replicate many features of the conventional labor control. For example, a) the ***selective projection of distinctive order opportunities*** that can be projected solely to one agent per case, b) the ***communicational isolation*** between the agents that work under the same platform "playground", and c) the disassociation that the software can nurture cleating ***virtual reality conditions*** that can replace the complex but pragmatic conditions of the real world, is a great tool which can either be used for good or for evil. It all depends on the quality of interests that the platform owner, usually a capitalist, wishes to exert upon the workforce. Whether enforced or not, the software (i.e. the algorithmic management) allows for the agents' puppeteering though the distortional lenses of the platform's digital properties. These are the fine limits that distinguish *workers* from *slaves*, *monitoring* from *surveillance*, *leveraging* from *exploiting*, and *controlling* from *enforcing*.

Even before the 80's, Michael Burawoy was suggesting that **hegemonic (authoritative) control does not necessarily yield a positive outcome** for the autonomous workers. It just helps to elicit their consent to exploitation. The **consent, he states, lies in the illusion of choice** although the activities of their limited choices is narrowly bounded. The gig workers, are outside of the social safety laws that could surround and protect them, they have no basic workplace insurance, no minimum wage guarantees, no compensation and no right to unions. The pace of work is not defined by them, and the same goes for their repertory and the place, or time that their tasks will be performed.

Regarding the algorithmic despotism, the authors of [78] found that all of the examined platforms are based in the rhetoric of flexible working conditions which helps recruiting and motivates investments. However, the freedom that they promise is, in every case, constrained by the algorithmic structure of the informatics systems in place. In conclusion, there were many workers who valued the flexibility that this kind of work could offer, yielding high significance to practices that support their autonomy. **Their freedom was mostly related to the lack of human mistreatment** (which most probably reflect to the breaching of social conduct barriers, like corporate culture, passive aggressiveness, superficial intimacy etc.) clarifying that they still valued accountability. This shows that **the benefits were not a direct result coming from technology but rather the lack of the inappropriate approach of a human figure of authority**. As the authors of [78] state, the freedom in many cases was experienced as the lack of a flesh-and-blood supervisor. On the other hand, this relative autonomy was perceived as the compensational price to be paid for the algorithmic control which is designed to support lack of transparency, incentive pricing, uncertain outcomes, schedules, nature of tasks, performance ratings, and unpredictable earnings.

The authors stress that future research should uncover the reasons behind the varying algorithmic despotism intensity in platforms of similar nature. This is a critical point as they emphasize the importance of adequately advising the respective political and legal debates to improve the working conditions and earnings of the platform workers, i.e., the delivery agents in this context.

#### 4.4.2. How History Matters

The work of 4.4.1 demonstrated that some of the logistic algorithm characteristics can be unfair due to design flaws or due to deliberate design choices. However, the paragraphs to follow present a series of issues that are actually attributed to specific innate properties of the algorithmic nature. The authors of [79] approach such a case, for the dynamic competition when network externalities exist. They argue that when a platform succeeds in dominating a market for some time then it starts becoming **'focal'** during the current period, i.e., the agents that join the platform are absorbed by the given level of equilibrium (mediocre – like the QUERTY case study or the Mandela Effect). Having established that idea they examine whether a highly-quality competition can change the status of the existing focality.

They find that **in theory multiple equilibria exist** (of many quality levels) where a platform can dominate. They also demonstrate that if the competitive qualities are stochastic then the platform that dominates is the one with the better average quality. This, in turn, means that social welfare may be defragmented and reduce in quality as the platforms become more forward looking (in the sense that they plan in a **presbyopic manner**, i.e., they take into consideration an infinite time horizon).

Among many examples one relates to the dynamic pricing competition, where the authors provide their main contribution, showing **that beliefs on the history of the market can detrimentally influence the competition of vertically differentiated opponents**. Over an extensive literature research, they conclude that their work is the first one that addresses the **consumer perception** according to historic events (expectation) and the ways it affects the various equilibria.

At first, they consider finite time horizon and show that there exists a perfect Nash equilibrium where a high-quality and non-focal platform dominates. However, unless the quality gap between the competitors (platforms) is large enough, the low-quality platform will dominate. They also examine the Markov perfect equilibria during games that extend to an infinite time horizon and show that **the dominant platform may not necessarily be the one of highest quality**. The most important part is that the dominance may be unrelated to the platform's base quality and regardless if it is forward-looking. The authors proceeded by replacing the concept of the network effects by switching costs and realized that this change a) eliminated the equilibria that were emerging due to excess momentum or inertia and b) the effective threshold in the quality gap between the competitive platforms increased. These shows why it is important to study the network effects isolated from the switching costs as these alone are capable of shaping the effective market preference (outcome).

Finally, the authors consider the stochastic qualities case, where platform qualities change over time. The results suggest that there is an equilibrium for every period (defined as the time between quality changes) that each competitive platform has a chance of dominating the market for that period. The important conclusion here though is that **the probability for an inappropriate (for the common good) platform to win increases as the platforms that care about the future also increase**. This also suggests that given the belief structure of this work's model, any positive expectations for the future provide substantial power for dominance. The platform that most individuals anticipate to be the high quality in the future can dominate today with a lower cost than the rest. This means that the incentive of the rest competitors to fight for the focal position today, is reduced. The results also suggest that when the consumer heterogeneity is increased (which is a realistic case but the installed user base is always a concern), the effects of focality are reduced and so the competitive platforms are less inclined to fight for a future focal position. Nevertheless, in all cases, the authors have confirmed that the expectations (history) can influence the excess inertia (future focal point) of the market and subsequently lead to reduced social welfare.

#### 4.4.3. Optimizing Central Routes

One first example of an algorithm that seems to produce **revenue inequalities** due to its design, is the one found in [80] which is focusing in optimizing the courier routes in places with high congestion like in central city areas. This work uses an algorithm that can create near-optimal solutions, considering environmental and operating costs. However, it does not consider the fact **that high congestion probability occurs in areas of high urbanization** which, in turn, leads to a high concentration of quality order opportunities, including the multi-bundle and multiple-destination ones. This is used as **an example of the greediness that an otherwise perfect algorithm can exert on fellow-workers of the same fleet** or even the competitor ones, who may be unfortunate enough to be located in the suburbs or a few miles out of the city limits.

This work uses a GA to provide the optimal solution assuming that the agents that are involved will either drive or walk if needed and will make use of multiple order or loading zones. The survey shows that the agents tend to use less loading zones and service many customers so the model was used to leverage a better exploitation of the given scenery and available resources.

One suggestion for **a future improvement towards holistic fairness** would be the study that **parametrically reshapes the specific algorithm** (using special weighting factors**) to either increase or decrease cooperativeness** (with agents from distant areas) and **use sensitivity analysis to check the influence of the increment of the delivery platform's reach and total revenues against its leverage to total fairness**.

#### 4.4.4. Encouraging of Real-time Scheduling

Similarly, to the principles presented in 4.4.3 the algorithmic design of the work in [81] is quite **monopolistic**. It is formulated considering the driver's perspective, aiming to guide the few fortunate drivers who are close to multiple opportunities (orders) to optimally serve as many orders as possible by maximizing their total earnings and efficiency (in terms of time pressure and distance). This is one more example of an algorithm that works best by helping the most privileged of the drivers to maximize their 'game' in an effort for the owner of the fleet to maximize the firm's revenues.

The model is designed on a Markov decision model, which is powerful **in sequential decision making problems**, where the rational driver is expected to operate in the principle of **maximizing self-interest** and assuming that per any given decision cycle, the demand, time pressure, speed limits and locations of the orders do not change.

The work of [81] used various order distributions to demonstrate that the algorithm can effectively and stably serve multiple orders, maximizing the firm's revenues by turning the routing problem (a multi-period immediate delivery problem, or a VRPTWDR) into a sequential selection problem as experienced from the agent's perspective.

Similar to what has been mentioned for [80] in 4.4.4., it would be interesting to examine the same problem from the point of maximizing fairness while analyzing the effect that various fairness (equity of income) levels would have on the total revenue.

#### 4.4.5. Just-in-time (JIT) Optimization

The work of [82] investigates the key factors that boost the success of an ODFD business and argues that primarily the algorithmic focus must be paid in speed, timely delivery and cost-effectiveness, especially **for covering the challenging large-scale orders**. The authors state the optimization must mostly cover the first mile (FM) and last mile (LM) parts, defining the objective as the minimization of the over Cost per Delivery (CPD) and the order delay. They create policies based on the Just-In-Time (JIT) concept which tries to match the time of production with the time of consumption. The authors characterize the policies as "**aggressive**", reporting promising results for the savings of CPD, which is achieved by minimizing wait time in order to keep the customer experience (CX) high. However, CX and CPD are opposing to each other so there needs to be a trade-off between the two. The problem is split into two optimization areas, as already mentioned, the FM challenge which is minimized by JIT and the LM challenge which is dependent of the best order batching and routing. The batching of orders reduces the CX so the ODFD system needs to be very efficient in order to keep a high rate of Orders per Day (OPD). This will stress the Driver Experience (DX) in order to keep a good level of service to the customers.

However, during the low demand periods, it Is best to keep batching low and provide orders to more drivers, which will increase the average income for the drivers and keep a good CX level. So, the authors understand that the main problem is the assignment optimization where the right batches will be assigned to the right drivers in order to minimize the CPD while keeping a good CX and DX. The authors propose a batching algorithm and an assignment model which is fed with real-order data. The simulations show that the aggressive JIT reduces wait time that is reflected in the overall CPD, even with the introduction with a CX cost. However, as they also state, there needs to be further research, among other batching and dispatching formulations, **to include the DX in the objective function**.

### 4.4.6. Challenging the fit-for-purpose concept

The work of [83] aspires to produce better solutions (regarding ODFD waiting times) in the cases of crowd shipping VRP, which are characterized by different start/end points, shifts, capacities and types of vehicles (VRPTW), through the utilization of an agent-based metaheuristic method. The cooperation of the agents would optimally reduce number of used vehicles, waiting times and travel distance.

The paper approached the solution to heterogeneity by introducing the multi-agent-based methodology and an evolutionary framework which lead to lowering the waiting times in expense to other objectives; mainly the travelled distance. When the authors conducted further experiments (modified MDVRPTW instances) they found costly deviations for all of the objectives. As a concluding remark, the authors understand and stress the requirement for future work that will focus on the **creation of benchmarks that can capture a well-rounded view of each scenario with realistic variants and practical modifying factors**. They also acknowledge the need for a systematic future research that will use parametric experimentation to allow for the metaheuristic concept to suitably find the best fitted algorithm to aid the model under examination (like, for example, the agent-based one that they used). In other words, there needs to be a systemic approach that will guarantee that the mathematical approach(es) used in the algorithmic solution process **are fit for purpose** and **honor the nature of the constructed model** (for example the field of application, the type and range of constraints, the characterization model and its parameters, the proper identification of the properties that lead to an enlightening sensitivity analysis, etc.)

### 4.4.7. Fairness Concerns Routing - Self-regulation with virtual incentives

One dimension of fairness, according to [84] is related to **the avoidance of algorithmic congestion trends**, as in high-concentration of vehicles where the solution process favors one specific route (for all vehicles) over all other alternatives. The idea is to provision for the effects that the quick response of (one or more) OFDAs may produce while trying to optimize variants of VRPs for a fleet. Regarding the concerns about fairness, from a rider's perspective, it is important to note that, **in order for the riders to execute the recommended path to balance out any congestion trends, they need to perceive their contribution as a worthy, thus accompanied by the respective payoffs in order to proceed with such a decision** (i.e. to select the alternative road).

The authors use a reinforcement learning algorithm to compensate for the unfairness that the existing solving theorems impose to the proposed solutions. The experiments show that the Nash equilibrium (i.e. the combination of strategies) coefficients all converge to 1, thus the approximated algorithm is confirmed to work, and the averaged fairness is increased (from 92% to 96% - for equal travel time) because of the **payoff policies**. Figure 14 summarizes the logic that the work of [84] has followed and emphasizes its twofold contribution scheme, in relation to the existing literature.

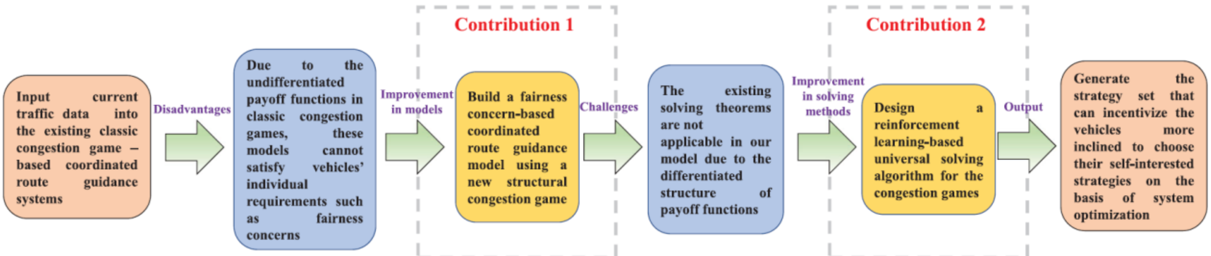



**Figure 14. Contribution logic of [84].**

The modeling approach used in this paper is a decentralized fairness concern-based vehicle route guidance (VRG) system which can be applied to an *Internet of Vehicles* (IoVs). The numerical experiments and the study of the results confirm the proof of concept as the improvement incentivizes the vehicles to select their alternative (self-interested) tactics, to be in accordance with system – rather than individualistic – optimization strategies.

A limitation of the work is related to the initial assumption of 100% penetration of IoVs, although in reality the IoV adoption will be gradual, which suggests the existence of a mix with human-driven cars in real scenarios. For this reason, the authors suggest **further research to be conducted on the stochastic IoV penetration rates**. The authors also advise for an extended sensitivity analysis in scenarios with larger networks and to include much more parameters in the mix. Also, they advise for the implementation of faster reinforcement learning algorithms as the agent-based model of a larger smart-city will turn into a challenge of a much larger scale.

In other words, the authors state that the VRP algorithmic solutions, can in some cases, be objected to the selfness that emerges as a property of the optimization routing algorithms, which in turn creates high concentration of competitiveness in specific areas (expressed as congestions). This can be avoided by compensating awards which are designed to be valued as much as needed (which is a calculation facilitated through a Q-learning based algorithm), in order for the individualistic vehicles to value the decision of an alternate route selection as worthy. This, in turn, increases fairness and improves the efficiency of the system.

This is like a system that self-regulates the dynamic response of its routing optimization technique, which, if left uncontrolled, may lead to suboptimal solutions by injecting a higher virtual incentive that will re-create aggressiveness on the optimization. The virtual incentive is designed to cost no more than the cost of a greedy system where no regulation is applied, and all possible congestions have been completely formed. On the other hand, it is not easy to locate the value of the virtual incentive over which the system deviates to a suboptimal solution due to too much alternate routing diffusion.

# 5. Showcasing the main challenges – Introducing Fairness

## 5.1. Main Meal Delivery Routing Issues

### 5.1.1. Formalization of Challenges, Performance Metrics, Features and Policies

The authors of [85] have made an extensive study on formalizing the Meal Delivery Routing Problem (MDRP), investigating the most regularly used key performance metrics, the algorithmic features relatable to the nature of the problem and the various policies and their impact on the analysis of the final results of such problems.

The development of the respective algorithmic methods is tailored to face the challenge of optimal courier assignment, which falls under the dynamic VRPs and the capacity management (which can be managed by offline shift scheduling). The work of [85] investigates several instances of the problem using realistic size, urgency, geography and dynamism in order to confirm that the expressed ideas can offer solid solutions for real-world scenarios.

The authors acknowledge the difficulty of the problem due to the **dynamic nature of the emerging orders and the last mile logistics**. More specifically it is well established that the delivery agents need to respond to orders that may appear in a quick and sometimes abrupt, change of demand across a wide range of the spatial and temporal dimensions. Such problems fall under the dynamic pick-up and delivery problems (dPDP). The authors argue that in order for the emerging technology of the OFDAs to be economically sustainable, i.e. to provide adequate profits, it will need to be able to solve **increasingly complex dPDPs in real-time** and provide **high-quality results that satisfy the competency among 3rd parties and the evolving regulatory standards**.

One primary promising format that aspired to meet the desired responsiveness while keeping the employment and large-fleet maintenance costs low, was the adoption of the "gig economy's" "digital marketplace" business model, where the delivery agents are all engaging as independent part-time (or even full-time as it turns out) contractors (free lancers). This model managed to cover the initial hype in demand, as the introduction of that platform was anticipated to self-balance to a win-win status for all stakeholders, and settle to the necessary level through the so-**called indirect economic incentives**. This business model had been explored by the cab/taxi drivers, moving fixed costs but also autonomy, supporting individualistic behavior for better or for worse, per case, allowing for the ecosystem to control capacity, price and service quality levels in sync with the customer demands and expectations, over time and geography.

However, a full-reliance to free-lancers creates a fundamentally versatile operating environment, completely different from the conventional VRPs. The autonomy of couriers and the internalizing of costs and risks created an extra layer of complexity. This autonomy created uncertainty in scheduling (time and period of work), in dispatching (whether the agent will engage to servicing the order or not), and routing (as the agent can decide on priority of orders). The authors state that although these are challenging issues, **they do not explore the adoption of so flexible models, like crowd-sourced dPDPs**.

As the authors of [85] state, apart from defining the MDRP structure and emerging challenges in dPDPs, they have found that the decisions on capacity scheduling have a critical impact on performance and reliability while the meal preparation timings do not. They also claim that the proposed approaches can facilitate to dPDPs solutions despite their simplicity and myopism. In that note they introduce the "*myopic rolling horizon repeated matching approach"* which is a framework that has been tested and proven to produce high quality solutions **when there is low visibility to the emergence of future events**. An unexplored field is what would happen if there was no restriction in the vehicles being empty before starting a new pickup (and subsequently delivery), i.e. **what would happen when allowing for more relaxed routes**, balancing between the known trade-offs (delivery time, quality of food, number of orders services, etc.). Although the authors mention the idea, they do not employ it to their algorithm propositions. The next point in the same context refers to the information which can serve as stochastic knowledge and which can be used as an **indicator of the expected location for future points of interest** (pickup and delivery), calculating the cost of moving to serve the uncertain requests against the opportunity costs of losing valuable time while waiting still and missing the correctly projected appearance of a future order.

Another important issue is **the effective balance of covering current tasks while being flexible enough to easily serve all unknow future tasks**. A similar issue is to properly decide when to drop (actually postpone) and when to engage to the execution of an order or a series of orders, to manage the accumulating uncertainty. An approach that can to some extent cope with that challenge is the introduction of a *double horizon heuristic*, which evaluates and compares the cost of actions (drop-off or engaging to the order) with different cost functions depending on the time-scope of that occurrence (short-term or long-term, i.e. beyond the horizon). This technique was proposed by [86] and it outperforms the single rolling horizon methods especially for time windows from 1 to 8 hours. Its performance diminishes in relation to the single methods as the instances grow in number.

The authors of [85] discuss the definition of *effective degree of dynamism* which tries to capture the urgency and the change of information, all at once. They argue that *dynamism and urgency* are different in the sense that low dynamism and high urgency will lead to high costs but when both are high, they will not, and that high urgency along can lead to high costs, while cost is quite indifferent to changes of dynamism. An expression that can cover this case is that **a large number of dynamic requests can be serviced with good solutions as long as most of them are received (acknowledged) by the dispatcher long before their service time**.

As s summary, the main structural points of a MDRP are the **several pick-up points** (food & meal suppliers), the **dynamic order appearance**, the **capacity to be delivered**, the **courier shifts**, and the possibility to invest to **simultaneous pick-up and/or delivery** (*bundle orders*), per case. There are two real-life features which are not captured in most models and this is the ability of a courier to turn down the order offer and/or to relocate when in an idle mode (*prepositioning*). Also, it is assumed that deliverers cannot be diverted during servicing any particular order but only in the time slots between (*assignment updates*). Also, a real-life point is that couriers are most of the times allowed to drop-off items after their off-time.

The main performance metrics (measures) for the MDRP are: 1) the **delivered order count**, 2) the minimum, maximum and average total **agent earnings**, 3) the total **cost per order**, 4) the minimum, maximum and average **click-to-door times**, 4) the minimum, maximum and average **ready-to-door times**, 5) the minimum, maximum and average **agents utilization**, 6) **orders delivered per hour**, 7) **bundles per hour** (combinations of pick-ups and/or deliveries per hour), 8) the minimum, maximum and average **orders per bundle** and, 9) **delay penalties per hour**. Some relevant statistics that can be applied to the aforementioned measures also include the standard deviation, the median, the $10^{th}$ and $90^{th}$ percentile.

**The "lazy" commitment strategy** that is adopted in a rolling horizon algorithm tries to mitigate any uncertainty by **postponing non time-critical decisions**. The commitment shifts to "active" when there are time-critical decisions involved (singletons or in a bundle). The commitment is called two-stage additive as a courier is sent towards a specific area (or direction) of interest, with "partial" commitment, as this status may change in the next optimization round (for example while on route, the status of the rest of the fleet and/or the assigned path of the courier, can change to a level that requires for an alternative optimization which suggests the bundle composition to change). The "final" commitments are the ones which are guaranteed not to change.

Although the work of [85] does not regard the issues of equitable income fairness into the optimization mix, there is a mention on an important variable called **geographic dispersion** which captures the travel times required from a depot (restaurant) to the points of delivery and the travel times between any pairs of depots (restaurants). The aforementioned **dynamism** defines the continuity of the available information change over a planning period. The **urgency** captures the time that a delivery needs to be serviced in relation to the order's arrival time. The reaction-time is then set as "soft" or "hard" depending on the resulting urgency, per order. Finally, **flexibility** defines the available range of time for dispatching an order ensuring a satisfying quality of service.

A number of simulations (or actual real-life trials) using several **variations of the algorithmic parameterization** will most certainly lead to distinguish which properties are favoring the final results, and thus create a 'notion' of the best optimization strategy to follow, per case (i.e. per city, or area, as the MDRPs always assume a finite area of operation). Such configurations usually depend on criteria like the rules for bundling intensity (how open to many simultaneously to-be-served orders), for the assignment prioritization, for the commitment levels (as described), the granularity on the sub-optimal solutions per area-division, the fleet response, etc. Usually, when dynamism increases the fleet utilization and the bundle-volumes tend to decrease, while the cost of each order increases, as expected. The orders that arrive in bursts with high dispersity defer and discourage bundling, while on the contrary, the order bursts that come concentrated to a limited space offer high bundling benefits.

Taking into account all these, an extra useful property would be the idea of using a **re-configurable** algorithm which would base its behavior based on a series of metrics, by periodically adapting its parameters to better serve its purpose, per time and per location of operation. One important dimension of such a system would be the attention given to the agents' autonomy. A model that would **leverage the assignment rejection of an individual to counter-balance the common good and vice-versa** would be a fundamental step towards the dynamic stochastic solutions of such problems.

### 5.1.2. FoodMatch – Batching and Matching for OFDAs in Dynamic Road Networks

According to [87], given a food ordering stream, the key decisions to be made are the order assignment per agent (vehicle), the grouping (batching) of meals/orders per agent (depending on capacity to cope with vehicle availability), the adaptation to new positions and the stability of demands to the evolving (daily) work-loads. The authors of this work develop the **FoodMatch** algorithm that formulates the challenges as a *Minimum Weight Perfect Matching* (MWPM) on a bipartite graph. The computational cost is further reduced by deploying a *best-first* search to focus on the subgraph that is most likely to include the minimum matching goal. Furthermore, the quality of the solution is improved by reducing the batching to a problem of properly projecting the dynamic positions of the agents based on *angular distance*. Figure 15 presents the pipeline of FoodMatch.

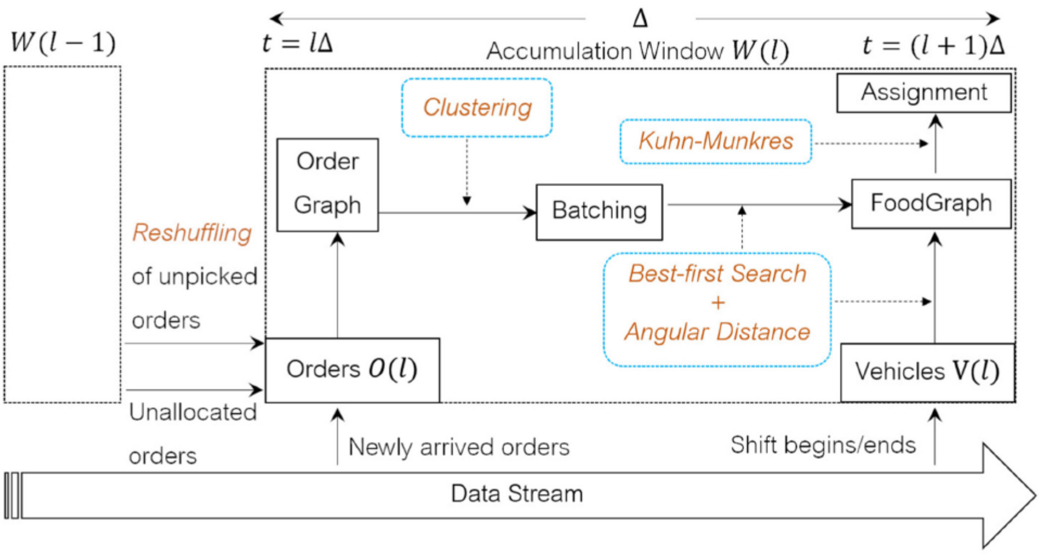



**Figure 15. Flowchart of FoodMatch**

Given an order stream and a number of available agents (vehicles), they are regarded as accumulated by the process in windows of length Δ. During the current window W(l), the V(l) is collecting all the agents that are available and O(l) gathers all the unasigned orders plus the ones that have been assigned but not picked-up yet. The O(l) is next batched. The bipartite graph is created by those batches and the V(l) agents. The first-search expedites the graph and, in addition, the dynamic movement of the agents is incorporated through angular distances. The MWPM is then applied using the Kuhn-Munkres algorithm. The process is run for each Δ to adapt to the dynamic stream environment. The algorithm makes use of Swiggy datasets reporting a 6-fold cross validation and after 5 days of training it settles to the proper parameters estimating travel times per edge, food preparation durations, etc.

The algorithm is then compared to two well-known algorithms the Reyes (as shown in [85]) and Greedy. The Reyes one does not incorporate the road network to calculate distances but it uses haversine distance and the batching allowed through the linear programming formulation cover only orders from the same depot (restaurant). For that matters, Reyes misses about an order of magnitude more manhours than FoodMatch. When compared to Greedy, the delivery time of FoodMatch results to be about 30% better. It seems that FoodMatch reaches the global objective better through the MWPM and is able to cope with scarcity of agents in an easier way, too. Also, FoodMatch seems to be delivering 20% more **orders per km**, which is due to the dedicated batching component of the FoodMatch method, as shown in Figure 15. It also reduces the waiting time at depots by approximately 40%.

As to the future work ideas, the authors of [87] states that the specific challenges are multi-stakeholder problems where each player obeys/serves it own objective functions. Thus, it would be nice to use a set of objective functions that would correlate in a way that can apply to several (and versatile in nature) stakeholders. So, it would be interesting to explore methods which can jointly improve all metrics of interest for all stakeholders in a win-win-win- situation. This may be done using a weighted sum of objective functions with a relative weight that would depend according to its importance to a higher entity (minimization of overall cost, maximization of service quality, minimization of time spent in work, minimization of food degradation, minimization of emissions and fuel consumption, etc.). Another approach would be to create a Pareto-optimal front of solutions and a decision support system that would decide which property is the most fit for granting it as carrying more merit that the rest.

### 5.1.3. Occasional Couriers (Crowd-Shipping)

The authors of [88] investigate the viability of a “courier friendly” scheme that will be based on **crowd-shipping** (CS) model in order to cover the express package deliveries in urban locations. That novel idea is to use transshipment points to facilitate the operability of the system, using a company-managed reserve to backup any uncertainty to the crowd-sourced fleet.

The algorithmic approach is based on dynamic programming (DP), without assuming any specific distributions and demands. The authors study various extensions to consider the constraints of the fleets and the point capacities and use the information of the agents that declare their arrival to use it in its advantage. This particular study is the first example of employing a Monte-Carlo approach to calculate the “shadow costs” of capacity limitations and utilization and exploit this knowledge to improve the assignment (matching) of the service’s decisions. This paper offers insights on the potential strengths arising by delivering packages through the (central) **coordination of** occasional couriers, the evolution of the **transshipments** under short delivery requirements, the impact of the temporal and spatial distribution of the emerging demand and agents’ arrivals on the overall performance and the contribution of the timely notice of the agents arrivals.

The specific model formulation can be regarded as a two-echelon last-mile delivery system where the primary operations (initial and final pick-up and delivery from door to intermediate service depot and from intermediate service depot to door) are covered by the customers or a dedicated delivery capacity and the secondly operations (between the intermediate service depots) in covered by the CS platform.

Regarding the realistic implementation of that scheme, it will be nice to consider eco-friendliness and cost effectiveness by the employment of lightweight electric vehicles, bikes, aerial drones, etc. in the primary echelon transfers to enhance the benefits of the CS approach and open up this field of study to new research directions regarding novel ideas in city logistics.

#### 5.1.4. Delivery agent scheduling in O2O business

The study in [89] is investigating the non-uniformity of the delivery agents in time (surplus or unavailability), as there are numerous of independent restaurants (depots) that compete for placing and servicing their order in the OFDAs and the demand fluctuates both over time (periods of burst or inactivity) and region (rural vs. urban).

In order to cope with the issues that this non-uniformity creates, and the potential drawbacks that this introduces in the logistics flow, the authors of [89] introduce a two-stage model for proper agent (here called rider) scheduling. The model adopts the mixed-integer programming (MIP) method, then characterizes various relevant properties of the scenario and makes an optimization plan suggestion for the agents' scheduling. In order to achieve this, the method **divides the available time and region into smaller parts**. The goal is to provide a high level of delivery service at a minimum cost. **The algorithm considers for every sub-region a dial-a-delivery rider model** (which is the first stage of the method**) and then a transportation capacity allocation model is used (that utilizes the second stage of the method) to reduce any imbalances**. The calculation challenges of the first stage are tackled with the development of an *Adaptive Large Network Search* (ALNS) heuristic. The second stage is solved using Gurobi 9.1.

The findings show that the tightness of urgency and the fleet count are closely related. A tighter time window requires more delivery agents and means fewer orders per agent. **In terms of agent capacity this work focuses mostly into how to divide the region into sub-regions** (regardless of the rider's familiarity which increases for smaller sizes and reduces total distance) and **how to separate the planning horizon to smaller periods according to the demand**. So, the authors acknowledge that there are many directions to be researched, like the **division according to historical fluctuations per area**, considering the peak and off-peak periods (weekdays, holidays, etc.) and the **uncertainty in the delivery process** (due to unexpected traffic conditions, etc.).

### 5.2. Cooperation and Corporate Responsibility

#### 5.2.1. Third party partnerships – A DSS for restaurant owners

The work of [90] investigates the idea of 3rd-party partnerships with a delivery service, based on the urgent need of restaurant owners to invest into such contracts during the outburst of the Covid-19 pandemic. The authors develop an integrated prediction-decision model that analyses the alternatives, which are either establishing a partnership with an online platform (an aggregator), form a delivery team, or do both.

The tool calculates the profit of combining the two extremes and expresses the best decision policy in needed number of drivers, per case, given a stochastic demand. The authors use the *susceptible-infected-recovered* (SIR) model to forecast the pandemic infection and structure an autoregressive-moving-average (ARMA) regression model to predict the demand. The stochastic integer program optimizes the delivery plans according to that demand samples. The idea is unrelated to the demand feed that it receives, so it can be independently used for various unexpected demand surges and patterns.

The results of the decision support tool that was created suggest that a restaurant could benefit from a 3rd-party delivery partnership when: i) there is a low subscription fee with non-binding terms, ii) the customers are allowed to decide if they can order from a platform or directly from the restaurants, iii) the end-user demand (customer) requires efficient delivery schemes and reciprocates for that iv) the delivery distance is not negligible but rather long, and/or v) the variance of demand is high.

#### 5.2.2. Many-to-many Food Delivery (On demand)

The Covid-19 pandemic had (and to some extent has) disrupted several supply chains, among which is the On-demand Food Delivery Services. The respective industries have witnessed an enormous change in their operations. The research however has been limited to the one-to-one and many-to-one solutions which do not apply to systems where multiple customers issue many on-line requests from multiple restaurants. The authors of [91] analyze such cases, assuming good weather and normal traffic conditions and constrains that are formulated as multiple KPIs, like fleet utilization, delivery time (average) and fuel consumption costs. The same research also benchmarks the queueing methodologies using agent-based simulation and system dynamics modeling, including the *FIFO*, *Nearest and Simulated Annealing* (using AnyLogic).

The results of the cost analysis showed that out of the four delivery models that were examined (one-to-one, many-to-many FIFO, many-to-many Nearest and many-to-many

S.A.) all **many-to-many are most cost effective** than the one-to-one (given a clear variance in cost values). The **many-to-many strategies are improved with the addition of intelligent delivery techniques**, which can be seen by the many-to-many Nearest performance. As shown in Figure 16, the regression coefficients show the increase in cost over time which helps to rank the models according to their cost.

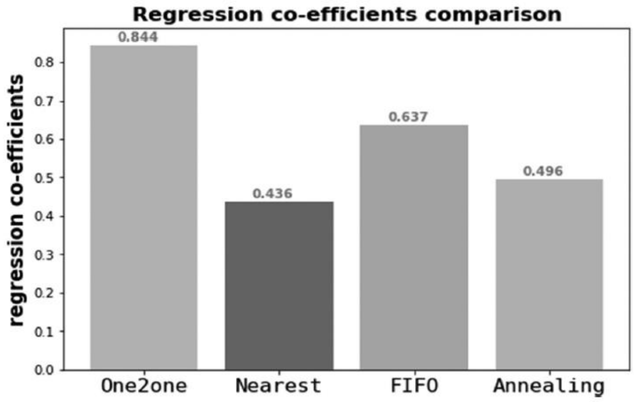



**Figure 16. Regression co-efficient comparison.**

The automation of the assignment process can be facilitated with a machine learning clustering technique, with each cluster assigned to one or more agents (vehicles). The many-to-many models can be further optimized for cost with optimal routing and scheduling methods.

The authors have not examined traffic or weather conditions and have not included the customer satisfaction as it focuses around the delivery time-window. However, they feel that this work can be perceived as a stepping stone in the field of many-to-many VFCDPs. The aim of the work was limited to highlight the profitability margin (and a basic sensitivity analysis compared to the fleet volume) as it emerges through the many-to-many models. These models not only affect system efficiency and transportation costs in a positive way, but also **enable better utilization values for the delivery agents**.

#### 5.2.3. Joint Distribution and Multi-Temperature Food

The joint food and meal distribution schemes, like the ones formed by the many-to-many strategies that are mentioned by 4.1.6, usually require special treatment due to their variety in temperature preservation until their reach the destination end-points (consumers). Especially the fresh, refrigerated and the frozen food (beverages, coffees, ice-creams) pose a high stress on the low-temperature logistics, let alone when these need to be combined with the usual meals that need to be preserved around 40 to 50 degrees when served. The one end covers the problem by the use of different temperature containers. The other end, is where the works of [92], [93], [94] can contribute the most, by examining the optimal delivery cycles [92], the forecasting of food quality in every stage of the cold chain [93] and the estimations on the optimal order quantity to be stored (in order to cover the managerial insights of the inventory issues) [94]. In more detail, the work of [92] which focuses on the distribution challenges, analyzes the issue using *Traditional Multi-Vehicle Distribution* (TMVD) and *Multi-Temperature Joint Distribution* (MTJD) systems. The models assume various time-dependent demands, and time-windows and focus on delivering multi-temperature packets to various customers, while trying to ensure low costs and high quality of service.

The work of [92] succeeds in determining the delivery cycles and the dispatching lists for the delivery agents, confirming that **it is achievable for both roles** (carriers and shippers) **to follow plans that lead them to benefit from the collaborative joint schemes** where food of different temperatures is delivered in the same vehicle.

#### 5.2.4. Serving a Common Goal

One very promising approach which seems to outperform traditional solution methods (on both cost and runtime) is the one described in [90]. The authors of this paper introduce the idea of ***multi-agent routing*** (that evolves on a neural network model) that acquires useful routing knowledge helping the agents to *communicate and coordinate their plans*, adapting to the traffic changes. Figure 17 presents a visualization of such routing.

**Figure 17. Visualization of the solution routes produced for a fleet of 20 coordinated agents (vehicles).**

According to the authors, the idea of routing multiple agents to cover a single common cause with a coordinated manner and a frequent adaptation to the conditional changes, is what is responsible for the performance of these results. The main advantage of this idea is that is **paves the road for the future world order** where autonomous robots will be ubiquitous and the primary focus will probably be the optimal management of such fleets.

The effectiveness of the proposed deep neural net called *Multi Agent Routing Value Iteration Network* (MARVIN) is based on the samples of road maps of 18 different world cities, which contains local planning in iterations of inter-agent communication through a special (asynchronous) protocol based on the attention level of the agent.

The topology of the road network is based on a graph analysis method (and logic module) called Value Iteration Module. The calculations are done using the Floyd-Warshall algorithm in order to create a dense adjacency matrix which results to better planning than the more conventional binary connectivity matrix of GVIN shown in [95].

The path planning is based on **deep-learning neural networks** which injects specific biases. The gated path planning networks use instead of a max-pooling layer, a generic *Long Short-Term Memory* (LSTM) design that improves training stability and extends the iterations count. Figure 18 presents the proposed model breakdown of its three main concepts/modules.

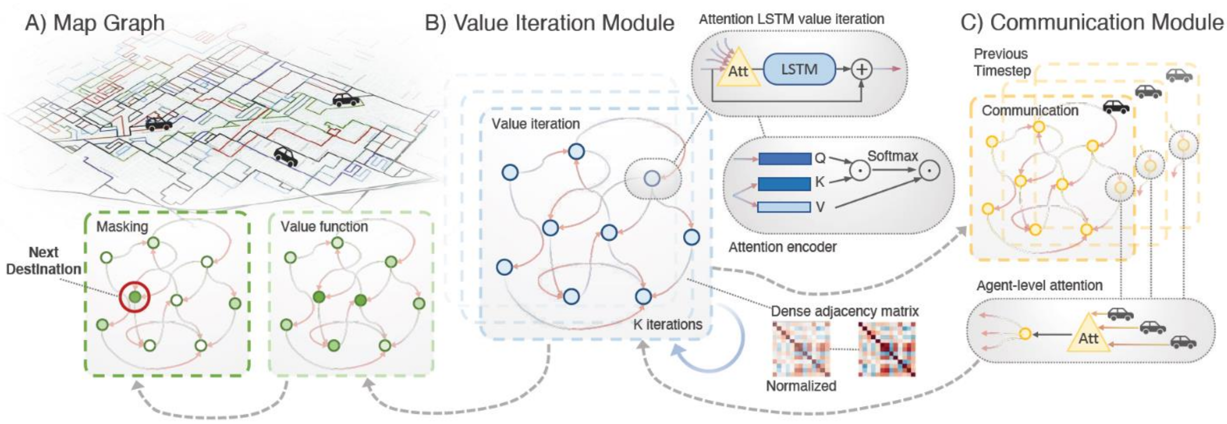



**Figure 18. Proposed multi-agent routing value iteration network: A) map representation as a graph with local observation features B) Each agent operating in its own value iteration network – uses LSTM to exchange information, evaluate and select next move C) Inter-agent communication.**

The ecosystem around this model assumes dynamic challenges in realistic mapping, and thus is able to perform in state-of-the-art road graphs. It is proven to be able to generalize to various numbers of agents and nodes without the requirement for re-training, which subsequently, renders it as a highly scalable model.

The same ideas fully support the hypothesis that a) pre-planning through an *Artificial Intelligence DSS* (AI-DSS) and b) inter-communication of the agents (vehicles), for example through 5G, can be advantageous to a fleet that wishes to serve a common cause. **This information exchange can be applied in a machine-based layer, where a specialized algorithm with an encrypted communication protocol will govern the overall planning**. This way, the fleet can still be human-based, providing extra dynamic input, thus enabling the reception of high-quality dynamic training information, without leaving any space for idiosyncratic divergence from what is collectively decided.

#### 5.2.5. Automated Negotiations in a Competitive Environment

Towards the **rationality vs. optimality** of the multi-agent vehicle routing negotiations, the works of [92] and [93] investigate an issue which requires engagement with three knowledge areas, the ***Automated Negotiation***, the ***Multi-Objective Optimization*** and the ***Vehicle Routing Problems***. The idea is that under an environment with multiple competing logistics the companies can still cooperate by delivering truck loads to one another with the common goal of improving efficiency (for both and not just overall) and reducing the fuel consumption (both and not just overall). The authors of this work well able to create a heuristic which can receive a set of delivery orders from each company and output a set of Pareto-optimal (and in every case rational) solutions.

The experiments that were run using real-world data confirm the applicability of such a tool as it can find hundreds of viable solutions in a few minutes. The problem is dealt as a CPDPTW with the aspiration that the system will be used in real-life applications. The idea is based on the assumption that each member of the cooperating alliance of companies will be agreeing to the disclosure of the customer's locations (and maybe to a few types of operational processes). **The mutually beneficial solutions can be accepted or rejected in real-time and the field of a-posteriori balancing negotiations is open since there is a range of viable solutions available in the Pareto-front for most cases**. The negotiation strategy can also be predefined so that the results will always be realizing a very specific point of that front, for every case. This then leads to a solution that includes a compatible order-vehicle pair based on the initial fleet schedules of each company.

Regarding the time complexity, for $m$ companies with $X$ orders each that involved $Y$ vehicles in their schedule (each), there are $m \times X \times (m-1) \times Y$ potential order-vehicle pairs. The time complexity is $O\left(m^2 \times X^2\right)$. The idea is that a significant fuel consumption and delivery time reduction can be achieved when some locations to be visited are close to each other. This leads to clustering where a *donating vehicle* from the donating company will cover the cases for both companies. Also, the same idea applies for the *receiving vehicle* and its schedule and the idea of a *one-to-one feasibility* is introduced if **such an exchange can be regarded as possible and fair**.

The authors claim that when the constraints of the companies are not too strict, the results can be fast as the algorithm will not be stressed to prune the whole search space. When the problem is examined from a single agent, the goal is for that vehicle to find all the respective proposals for cooperation and use them for the negotiation algorithm. This view allows to the specific tool to be used to any negotiation domain i.e. a space that includes a finite set of agents, a set of potential proposals (the agreement space), a set of utility functions (one per agent) and a set of reservation values (one per agent). The utility functions are the ones that can be defined by multi-variant aspects, one of which can be a fairness (global or local) factor like the one shaping the notion of equitable income.

### 5.2.6. Cooperative Reinforcement Learning (MAPDP)

On a similar fashion, the work of [94] is investigating the cooperation on multi-agent pick-up and delivery problems (PDPs) by the use of reinforced learning. The authors locate two major problems; the first being the structural dependency of the cooperative pairs that requires a customized model per case and the second being the difference of the vehicles of the two fleets that bounds the solution exploration.

The authors first design pairs that will yield the dependency exercised per included node, then according to the (structural) limits of this pairs they utilize of cooperative multi-agent modules that try to compensate for that dependence, and finally, they create the cooperative *Advantage-Actor Critic* (A2C) algorithm that trains the integrated model through a policy gradient approach. The multi-agent reinforcement learning is based on the formulation of a sequence generation process which is modeled as a *Markov*

*Decision Process* (MDP). The key elements of that process require the *State* of each agent, the *Action* at step $t$ for each vehicle agent, the *Transition* between states (action), and the *Reward* (characterizing the routing quality).

The proposed solution, with an added mask for feasibility, presents a small improvement when compared to other heuristics (1.64%) for which the vehicle assignment has been set in the order that they would take turns to be assigned to the decoded nodes. These heuristics were the *Ant Colony Optimization*, the *Tabu Search*, *OR Tools* – created by Google in 2016, the *RL-VRP* by Narazi et al. in 2018, the *AM-VRP* by Kool et. al. in 2018, and the *MDAM* by Xin et al. in 2021. The proposed cooperative algorithm (MAPDP) presented the best solution quality, however **its great advantage is regarded its small computational time since it created solutions 400 times faster than the second best** (for the case of N delivery and N pick-up nodes = 50 each, or 2N=100).

### 5.2.7. Peer-induced Fairness

One very important aspect of the VRPs, that is directly aligned with the main theme of this review, is the **peer-induced fairness idea**, which in the work of [96] is focusing on the capacitated VRP scheduling (PFCVRP). The goal is to primarily focus on the needs of the customers, by using a coefficient that is proportional to the population size and inversely proportional to the travel time needed per case. This is the modeling of the 'fairness' concept proposed to be used in *emergency material delivery*, along with *timeliness*, in such problems. The tool created by the authors, that aspires to provide well fitted solutions to such a formulation, is a variant of an *Ant Colony Optimization* with a *Variable Neighborhood Search* (ACO-VNS) algorithm.

The comparison results (for both small-scale and large-scale cases) with CPLEX (and other common optimization algorithms, like ACO, GA, ACO with 2-opt) **confirm that the ACO-VNS performs better as it provides faster (an order of magnitude or more) and more efficient solutions for emergency relief distribution**. Also, the comparison shows that the proposed algorithm provides very good convergence, for various numerical sets.

The authors' remarks regarding future enhancements and further research are targeted towards a) finding additional sets of valid inequalities to enhance the models, which is part of the focus of this review, and b) adding more uncertainties to the road interruption, such as traffic congestion and other conditional uncertainties.

## 5.3. Solution approaches of Prior Art

### 5.3.1. Attempting Fairness – A case study

Along with the raise of the OFDAs, a number of concerns have begun to emerge regarding the terms and conditions of employment for the "Gig economy" workers, which is the foundational human capital for the sustainability of that growth. In the work of [97], the authors acknowledge the issue and establish that this is not just an *NP-hard* problem, but also *unable to approximate in polynomial time*. The authors created a special algorithm to tackle the computational complexity of the problem, called **FairFoody**. They also used real-world data and conducted extensive experiments, demonstrating an exceptional performance of the algorithm, which outperformed the baseline strategies that it was compared to. The algorithm was able to improve the equitable income distribution to a great extent, with minimal impact on the user (customer) experience.

The 'gig' nature of the delivery agents is usually based on a fixed-commission payment per order (apart from the occasional tips or rare employment benefits). The OFDAs trend, which became much bigger during the Covid-19 pandemic, has provided many opportunities to the business owners of the restaurants but at the same time became a livelihood plan for thousands of workers in the food delivery industry. An independent survey in 2021, held by the non-profit platform FairWork [98], found that although the nature of the delivery agents has shifted from part-time occupation to full-time employment, with the workers investing their time and effort, fully engaged, treating them as stable jobs, the denoted associative idea is kept the same, highlighting a range of issues accompanying that notion, as **to non-transparent and thus poor working conditions, luck of health insurance plans, low wages, long working hours**, etc.

Regarding wages, an attempt to reduce the agents in order to increase the payment of each agent would result to a shortage of service and increased customer wait time. If the extra payment is moved to the consumer side, then, the extra charges will affect the customer base of the smaller restaurants. FairWork seems to support the idea of great inequalities among the monetary value earned by the agents through the OFDAs, and also by the OFDAs themselves. When looking at the number of hours that each worker has put in the platform, the inequality of profits per time division is quite obvious. And this is also supported by the actual claims of the workers themselves. The actual **location of operation can make a great difference**.

The FairFoody algorithm addresses that issue by redistributing fairness for an equalization to payments, for all. The algorithm abstains from moving the workers across zones. On the contrary, it creates limits to keep the range of a delivery agent small, so that a delivery agent will be able to pick and deliver an order on time. The fairness is injected by creating a uniform geographical distribution to the activity of the agents. This means that the implementation will be very helpful for the cases of metropolitan centers.

The authors, based on the FairWork's findings, which state the shifting to a full-time job engagement from most of the workers, base their algorithm design in amortizing fairness over the whole day rather than focusing in being fair for each and every assignment. This means that if an agent does not receive a fair share of delivery assignments in a given time slot, the system will ensure to make up for that loss on a future time, thus equalizing the shares of all, in the long term.

As to fairness by definition, there are 3 approaches that can be essentially regarded as re-distributing income opportunities for the delivery agents. The idea of a fair distribution has been studied quite extensively by moral philosophers, and particularly in Distributive Justice. There are three key principles on that matter which need to be considered.

The first one is defined ad ***Strict Egalitarianism*** which adopts the idea that **all people are morally equal and this means that all should be treated equally**. Porting this mindset in the platform would suggest that all players should earn the same income. One implementation that would cover that case would need to collect all fees and then share them equally to all agents. The 'gig' nature of this work however, would project the inequality of opportunities and would lead to inequality of effort.

The second refers to the ***Difference Principle*** as defined by John Rawls in 1971 [99], where **a system is just if anyone who is affected (influenced) by the system also agrees to be subjected to it**. For Rawls any inequality can only be allowed if it provides greatest benefit to the once who need it the most, as least privileged of society. If this is ported to the OFDAs it will mean that anyone with low income will get the next order, without considering the inequality of hours of the people working on the platform.

Finally, the third, which is referred to as '***Luck Egalitarianism***' is mentioning **complete equality as what would happen if sheer luck is completely out of the picture**. This will allow people to be impacted by their choices and pure hard work. In that sense, the porting of this mindset in the OFDAs suggests that the agents will be paid proportionally to their effort (hours of work). The authors of [97] call this ***Proportional Equality*** and use this approach as the best one to be used by FairFoody.

The actual algorithm is based on building a *weighted bipartite graph* with the *available agents (vehicles)* in one partition and *clusters of orders* in the other one. The weights of the edges that connect the two partitions (assignments) are calculated so that a *minimum weight matching* will optimize the Fair Income Distribution Criterion while ensuring a good solution for the Customer Experience Level without considering the driver's experience. The minimum matching is calculated using the *Kuhn-Munkres* algorithm.

The experimental evaluation showed that in terms of fairness, customer experience, and effort of agent (Gini coefficient, Delivery Time Per Order (DTPO), SLA Violations, and Spatial distribution distance) FairFoody outperformed FoodMatch and 2SF, across the income gap and the Gini index and came last to the DTPO and the SLA-V, but with a small difference from the rest. In fairness (as established above) terms FairFoody is performing better by an order of magnitude from FoodMatch and baseline approaches, as in the cab-service industry. In terms of the cost of fairness Fairfoody is comparable to FoodMatch. As to scalability, FairFoody is very efficient in large metropolitan cities.

FoodMatch seems to be focusing **mostly in minimizing delivery time and neglect the driver's income issues**. Also, 2SF is designed to ensure a two-sided fairness but in another industry, the cab driving, so it is optimizing the driver's income in respect to the waiting time, from the customer side.

In summary, the authors of [97] have contributed by a) **demonstrating that the levels of inequality exist and are quite high, especially in large metropolitan cities**, b) **formulating the multi-objective optimization problem taking into consideration both the (meritocratic) equality of income distribution and the customer experience** and c) **establishing that this concept can be applicable and successful to its objectives**. An issue is that the simulation of the FairFoody design includes all orders, restaurants and agents as prior knowledge, solving a deterministic problem, without provisioning for emerging accidents or stochastic behaviors like competitive, or off-the grid acts (i.e. compensating for various uncertainties).

### 5.3.2. Overcoming delayed Network Effects (Pricing or Time-to-market)

It is important to keep in mind that the pragmatic implementations of the OFDAs will be commercial products which not only need to provision for emerging uncertainties but also to compete in the same field of service, an actual modern arena. Like all innovational products, such an application will need to scale up against well-established brands (aggregators in this context) and to stand out, if and when possible. One important issue for that matter is the **adoption rate of the proposed new service** and this subsequently means that the network effect phenomena is best to be taken into consideration, to search for methods and tactics that can lead to high numbers of users, as quick as possible.

For that purpose, the authors of [100] are examining the influence of the delayed network effects which suggests that the increased product value and/or any additional user will be perceived with a slower than anticipated pace, delaying the product life cycle. In their study they research the best product introduction strategy for two information goods (of differentiated quality) on two different periods during which both will suffer from the delayed network effects. The firm is free to decide which product to release in each period and on which price. The authors discuss four strategies. The first is '***free trial*** which means that both products get released but the one (of least quality) is for free. The second is '***shelving***' where the firms releases the product of least quality during both periods but the best one only during the second period. The third strategy is referred to as '***combination***' where both products are released for free during the first period and then the best one is released alone and sold during the second period. Finally, the fourth strategy is '***versioning***' where both products are released in both periods but at a different pricing.

The findings of this work showed that if the delayed network effect is mild, it is best to adopt '*free trial*' to allow for the network size to expand, especially in the case that the two qualities differ a lot. If not, then it would be best to select '*versioning*' because this is what would create the highest revenue for each period. On the contrary, if the delayed network effect is intense and the qualities do not differ than much, it is best to choose '*shelving*' to take advantage of the delay of the network effects. If the qualities differ a lot (and the network effects are high) then it is best to choose '*combination*'. All cases are depicted in the clusters of Figure 19.

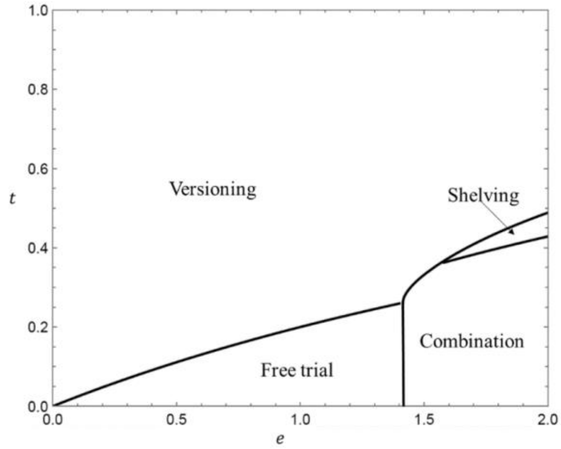



**Figure 19. a) Optimal product introduction strategy depending on the intensity of delayed network effects (e) and the quality of the low-quality product (t).**

Finally, the work of [100] showed that the choice of '*free trial*' yields the highest consumer volume and social welfare. The same work also investigated the optimal product placement under dynamic pricing. The canvas is split in two dominating strategies in that case. When the delayed network effect is not too high, the firm switches from '*free trial*' to '*versioning*', especially when the qualities become similar. The company will choose '*free trial*' if the delayed network effect is high and the qualities of the products differ a lot.

### 5.3.3. Last-Mile Delivery Approaches

The logistics of the last mile are quite challenging as they are highly influenced by the urban activity of today's city-structure to the point that this part of the supply chain becomes fragmented and subsequently very inefficient. In order to create more sustainable *Last Mile Logistics* (LML) the work of [101] prompts towards the examination of the main characteristics of the problem. In overall the author summarizes that the LML is affected by a high degree of granularity and thus variance of flow blocking actions and the employment of low volume (capacity utilization) and speed trucks. The author is classifying the main challenges into 4 categories, the *economical*, the *managerial*, the *infrastructural* and the *technological* one.

The cost relates to the attempts of delivery at customer's home (which cancels the benefits of retail deliveries), the management of the vehicles in traffic, the high fuel consumption, the higher risk for an accident. The alternatives that lead to the use of electrical trucks or bikes still leads to indirect operational, maintenance, storage and inventory costs, respectively.

In terms of infrastructural limitations, the inaccessibility due to road blocks, traffic jams, changes of directions, lack of parking slots, tight streets, and the geographical versatility of many areas make the use of a bicycle a required but inefficient solution, too.

From a managerial point of view, there are dynamic conditions (like conflict of interest, and lack of proper interaction between a plethora of actors) an issue that cannot keep up with the customer's expectations. The strict time slots (time windows), the mismatching of the orders' volume in respect to the expected distribution flow and the available capacity, and the marginal benefit per case, all contribute to frequent management failures, especially if considering the impact to the environment in this context.

As to the technological aspect, the electric bikes and electric cargo bikes travel at around 24 km per hour which is most cases is adequate but limited in capacity. This is why for the cities there is the prospect for shifting to the droned-based distributions. The current issues with the drones relate to the limited service area, the regulatory frame, the low autonomy when compared to other mediums (as they need frequent recharging), the noise and privacy issues.

The gap analysis conducted by the author of [101] has concluded that most of the literature is split in focusing on quality and VRP or on environmental issues and VRP. Also, most perishable delivery VRPs assume that each origin-destination is connected by an arc which defines the optimal path but this model does not completely reflect a realistic network. Additionally, **the service quality is restricted to the servicing under certain time-windows or refers to the quality of the products to be delivered, although there are many more factors that could, and probably should, be included as KPIs**. For example, the **working conditions** of the delivery agents, the **robustness of the service** against traffic uncertainties, the **social responsibility** (regarding firm competitiveness, driving behavior), the **customer priority based on personal behavioral traits**, etc.

The solution proposed by the author of [102] is to handle real time geographic data, assuming that such a promising solution like a *Geographic Information System* (GIS), exists. The proposal is implemented around an *Agent-Based simulation Model GIS* (ABM-GIS) which will be able to handle real-cases while operating in close distances but dynamically changing conditions between customers. The metrics to optimize against are selected to be the *Vehicle Hours Travelled* (VHT) and the Vehicle Kilometers Travelled (VKT). The impact of congestion is faced by introducing **short-term planning** while focusing on the calculating the optimal departure times from the depots.

Also, the ABM-GIS simulation indicated that the routes that include **multiple paths** or other attributes (places for short-term parking for example) and segments (cyclic areas, dead-ends, etc.) can help to alleviate emerging last-minute issues. For the cases with **soft time-window constraints** the Mixed Non-Linear Programming (MNLP) allows the reduction of the total costs (transportation, food degradation, time window violation). Another insight relates to the fact that an improved customer service to all other aspects can provide **an opportunity to stress the time-window constraint** producing a minimal impact on the overall user experience. Such a property may be exploited in cases where a small time-window constraint **may be the leverage of high reduction to the total cost** (considering all the implications to the rest of the future orders and also to the any incidents with potential drawbacks that would occur but can be avoided due to the acquired safe margins).

Finally, the customers' priority was taken into consideration (along with the time-window constraints) creating a meta-heuristic based model referred to as *General Variable Neighborhood Search* (GVNS) which focused in **solving quick sub-problems and collecting a solution set**. Then a posteriori method ranks these solutions according to a number of criteria. This means that a number of listings can be created allowing for a number of quick solutions as the problem evolves (but not in real time). The same idea was also adopted to approach a set of alternative solutions for the cases that add new characteristics of the real world into the problem and/or when the decision maker changes the specifications that define the quality of a service.

One idea that was out of scope but had to be stated is that the specific work would be very much enriched if the algorithms could process **real-time delivered data**. This would improve the quality of the VRPs and would enable the creation of excellent estimations.

Additionally, it would be interesting to examine a **Business to Customer market model**, (this was a Business to Business i.e. from the restaurant to the aggregator) as it is expected to grow fast in the future. Another idea that was mentioned is a reference to the **crowdsourcing delivery**. The author feels that it would be interesting to create algorithms that would be able to support such an evolving network.

On a similar study which was conducted for facing the last-mile delivery challenges, the authors of [103] suggest the use of a multimodal autonomous fleet based on a robot (autonomous ground vehicle) delivery system, a drone (autonomous aerial vehicle) delivery system and a hybrid delivery system (consisting of entities from both fleets). The design was run for 18 different scenarios which were simulated in MATLAB. The evaluation of the solutions was based on a *Level of Service* (LOS) scale, referring to the average waiting time of the customer. The results showed that the hybrid robot-drone fleet performed better. The next in line is performance was the drone-fleet and last came the robot-fleet. The assignment was not optimized, but it was rather based on FIFO. The authors suggest the use of a **p-hub optimization algorithm** which can be used to determine the best depot location for minimizing LOS while maximizing, optimizing charging times for the fleet and all in respect to the company's returns.

### 5.3.4. Multi-echelon distribution planning for perishable foods supply chain

Proceeding on similar concerns to p-hub optimization, the work of [103] studies the factors that best determine the location of cold storage and volume to be shipped in order to improve distribution lead time and supply chain costs. The research makes an attempt to examine a local distribution chain (of guava and lemon produce) to get valuable feedback on the applicability of the proposed method (based on *Mixed Integer Liner Programming*, MILP). The work proposes a tri-objective optimization model (reducing overall supply chain costs, cold storage cost and improve freshness of products) through a sustainable distribution channel. In order to deal with the multi-criteria challenge, the idea of weighted sums is used. The results yield various feasible options accompanied with the trade-offs that need to be taken into consideration when dealing with each one of the three aforementioned factors. Thus, the expert receives the proper aid from the decision support system, to help him/her employ the service to the most preferable location/s. Services like this one in [103] have the potential to provide great insights and strengthen the existing supply chain channels. They may even be able to contribute on understanding the unfathomable profit and quality improvement margins that most probably still exist in the cold-chain logistics of well-established retailers.

Food order assignment: On the problem of food-delivery, FOODMATCH (Joshi et al. 2021) is the only work to provide a realistic and scalable solution in food delivery domain. Other works on food delivery suffer from various unrealistic assumptions such as perfect information about arrival of orders (Yildiz and Savelsbergh 2019), ignoring the road network (Reyes et al. 2018), and ignoring food preparation time (Zeng, Tong, and Chen 2019).

For example, (Edelman, Luca, and Svirsky 2017) looked into the likelihood of racial bias in Airbnb hosts' acceptance of guests, while (Lambrecht and Tucker 2016) looked at gender discrimination in job advertisements. Few works have also looked at how producers and customers treat each other as a group. (Chakraborty et al. 2017) and (Suhr et al. 2019) proposed strategies for two-Sided fairness in matching situations, whereas (Burke 2017) categorized distinct types of multi-stakeholder platforms and their required group fairness qualities. Individual fairness for both producers and customers is addressed by (Patro et al. 2020) in tailored suggestions in two-sided platforms. De Spite these works on fairness in two-sided platforms, there has not been any studies on food delivery platforms. It is also worth noting that, as discussed in (Joshi et al. 2022), allocation algorithms for the cab service industry (Garg and Ranu 2018; Yuen et al. 2019; Ma, Zheng, and Wolfson 2013; Cheng, Xin, and Chen 2017) is not a natural fit food delivery.

By removing zone restriction, FAIRFOODY addresses the fact that the **spatial spread of orders is a key driver of unequal pay**. FAIRFOODY also achieves a fairer pay distribution by amortizing fairness over a reasonable period of time, thereby ensuring that agents who rely only on food delivery for their livelihood are fairly remunerated. Extensive experiments show that FAIRFOODY outperforms state-of-the-art baselines in lowering inequality while ensuring minimal increase in delivery time. Given the increasing adoptions of such platforms, it is the need of the hour and we hope that our work would lead to more follow-up works in this space.

# 6. Conclusions and Propositions Documentation

After a very detailed curation of all the referenced content, it is quite obvious that all of the algorithmic works mentioned in literature suffer from a common limitation, which in turn, is a result of the very complex nature of the VRPs. The computational power of the available technology today is not always enough to *adequately* grasp the wonder of a highly detailed model which, in theory, presents a non-deterministic polynomial time hardness. Besides, the granularity of any given model for any given challenge in science is as fine as the given mathematical tools can allow, **for the solution to be relevant to purpose** [4.4.6, 5.1.1]. However, the exponential nature of the networking relations in a VRP can quickly render any simplistic models to chaotic, hard (if not impossible) to solve formulations.

## 6.1. Most common challenges and Fit Solutions – A Systemic Approach

In order for the VRPs to be solvable but at the same time not too simplistic or generic, honoring the purpose of their creation, they are a-priori bound by design to investigate and be **sensitive to specific aspects of reality**, isolated from anything that would be regarded as a 'detail' or as an unrelated factor.

However, the issue that almost all of the VRPs are facing is how deeply **agnostic** they are in relation to the factors that their creators intuitively value as non-correlated or irrelevant. When it comes to the conduction of simulations or even experiments, the inability to know the magnitude of the information skewing in terms of solution credibility is stressed by the sensitivity analysis requirement in most of the referenced algorithmic papers. The most common challenges as these have been acknowledged by the authors of the reviewed literature are complementing their work with any of the following:

- *using coordinated heterogeneous fleet [5.2.4, 5.2.5, 5.2.6],*
- *serving multiple depot routes,*
- *servicing multiple products [5.2.3],*
- *taking into consideration demand/traffic/weather uncertainties,*
- *serving multiple (contradictive) objectives,*
- *optimizing for a dynamic pareto-front between (two or more) objectives,*
- *examining competitor response, and*
- *investigating the co-operation with subcontracting or external fleets [5.2.2].*

Even so, the reviewed works manage to include one or sometimes even two of these concepts in their module formulation and provide some very useful insights for the respective scenarios. After all, feasibility and practicality are more important and many of the analyses aim to provide **qualitative answers** to examine the use of specific policies or not, rather than **quantitative** which **is useful mainly for benchmarking** the performance of various algorithms under specific (and to some point unrealistic scenarios).

## 6.2. Externally induced properties – A Societal and Political Approach

The main issue, however, regarding fairness, seems to be primarily political rather than systemic, as there seem to be numerous claims leading to the conclusion that the platform labor inequality has been emerging as a feature rather than a bug [4.2.1]. There are 4 ways that immunize the restaurants and the platform owners from their obligations;

The 1st is the **misclassification** (through the platform's ToS, i.e. Terms of Service) of the hired personnel as independent (sub)contractors rather than employees of the aggregator or the restaurant [4.2.1, 4.3.1]. This lawful way avoids any compensations, insurances, benefits or ethical accountability regarding high performance stress. The platform promises flexible employment but the price is the direct absorption of all market risks and uncertainties which could be the responsibility of the employer [4.4.1]. The issues is related to the **unilateral discretion** of the ToS agreement which provides the right of modifications, at any time, to the platform, rendering the working relation asymmetrically dependable, and depriving any negotiating power from the worker, forcing him/her to retract from any future appeals regarding changes, regulations, decisions.

The 2nd is the **shifted dynamics in collection and display of information** for the favor of the platform rather the riders [4.2.1, 4.4.1]. The latter receive a competitive feedback compared to other workers or overall rankings, through the platform, with no transparency or linking to the real-world conditions which enhances the skewed platform-centric **utilitarianism** since the performance is evaluated by strict terms without considering the peculiarities of the surrounding environment, the challenges or the status of each worker [4.3.1], or what in short is described as ***Proportional Equality*** [5.1.1]. This creates a new audit culture where the collective perception interprets all actions as the new standard shifting the setpoint of optimal (or minimum) performance through **data-driven techniques**, according to the will (and the interests) of the platform. Obedience may be compensated by ‘instant task gratification’ perks, and dynamic price surges, however this does not relieve the tactic from its **authoritarian enforcing style that rewards out of the norm response** (usually in terms of speed, schedule, distance) [4.4.1].

The 3rd is the optional outsourcing capability, for example through the Customer Service Representatives “with terms that dissolve authority and accountability through the disinterested medium of a software program” [4.2.1, 4.3.1]. The platform uses internal enrollment techniques, creating incentives for fresh hires, **managing the turnover** so that there is always surplus of workers to cover demand keeping the underemployed workers on a level of **fungibility** and **superfluity.** As it has already been mentioned [4.2.1], this virtual depreciation renders the workforce an easily substitutable, abundant commodity through a central strategy that valorizes the tension of expendability and necessity by controlling hiring rates. The model that will ensure equitable labor conditions is not completely aligned with the intentions of high scalability and profitability which are the two main criteria that enable low-risk venture capital offerings.

The 4th is a perception that lies deep under the societal fabric as a controversial, ironically post-racial, and gender-neutral construct [4.2.1]. It is a trend that tries **to deface and dehumanize the offered service** using technological means to create perceptions deprived of anything that may implicitly remind to the serviced customers (as a sub-product of the neoliberal socioeconomic reforms) that the required service may be considered historically connected to degrading, underpaid, monotonous tasks (chores) of some nature [4.2.1, 4.3.1]. Apart from the ethical implications that such a tactic entails, its main effect lies in its corruptive power of **ghosting, isolating, and unconsciously discriminating** [4.2.2, 4.2.3] the workers from the societal forms that can acknowledge their issues and stand for their rights. As an example, it is apparent that this talk for the gig workers happens in forums, conferences and institutions, from academics, business consultants and/or policy experts, speaking for the life-struggling topics **of the under-represented gig workers**, who lack appropriate representation in general, let alone when discussing on platform-mediated labor issues.

The realistic, free of romance and wishful thinking approach, will be to experiment with novel platform architectures that are made to support co-operational and co-ordinational schemes, aligned to a social justice **that acknowledges the need, but does not conforms to the opportunistic logic of capital and market**.

The most hopeful and promising initiatives that can carry the burden of regulating and examining such platform acts, are **credible public institutions, supported by the respective ministries per country**, which will embed the values of alliances like the *Good Work Code*, in order to create unified legitimate entities that are self-sufficient, autonomous, and **strong enough to apply the software innovation changes required** [5.1.1], while pushing for regulatory, employee-friendly policymaking [4.3.2] and legislative governmental intervening actions that advance social care, morale and justice for workers, in a regular basis.

During this change, it is imperative to note that **such races need to be won in the digital arena too through process innovation** [4.3.2], and the work that needs to be done, especially for enhancing the transparency is through the **creation of a global database schema**, based on cloud services and special Application Programming Interfaces (APIs), similar to the one that allows for the transition from the Global distribution System (GDS) to the New Distribution Capability (NDC) for the air travel industry where the aggregators are reshaped to be uniformly compliant and controlled in fairness. Such a technology can allow for the existence of a framework over and through which all transactions will be regulated, as they will need to abide to the same rules, i.e. **well established and constitutionalized directions**. Although the schema is supposed to be openly available, the information and negotiations exchange [5.2.5] will be applied on a machine-based layer, including encrypted communication protocols, thus enabling the reception of high-quality dynamic information **without leaving any space for idiosyncratic divergence from what is collectively decided**.

The best part is that this proposition, **is not only promising a healthy social reform** but most importantly **lays on the feasibility of aspirations that are guaranteed to work**, since the GDS to NDC transition is already happening, on a scale and a complexity much higher than what is required for the OFDAs.

Over such a framework can be supported a series of additional plugins like for example one that would allow for **multi-sided fairness**, like FairRec [4.2.3], for a fair personalized recommendation system and algorithms that would allow for a minimum loss on the over recommendation worth.

Another example would be plugins that quantify the net-revenue and compare it against the occurrence probability of discriminative acts (on multi-stakeholder platforms, due to position bias, and/or monopolizing myopic client behavior), by calculating their actual cost in a CP-fairness fashion [4.2.2] (for example with the aid of a real-time data and statistics for improved estimations [5.1.1, 5.3.3]), and increasing or decreasing an avatar's exposure thus **regulating inequality, service quality and profits**, accordingly.

An additional example, which actually relates to the physical insurance of the riders **increasing social welfare** by minimizing traffic risk, is the regulating effort on spot check and publicity [4.2.3, 4.3.2] (which in the application it can be the obligatory engagement to a video projected on-screen campaign), according to the market size volume [4.2.4]. The applications directed, for example, by a civil protection service plugin, will alternatively adopt each policy (spot checking or raise of awareness through media) for a variable amount of time, depending on the received feedback by the riders, until the traffic risk rates are settled, per case.

On the same context, the same software can implement **lean management tactics** that will allow for the minimization of waste by introducing penalties when the system senses an opportunistic tactic by the platforms and/or by encouraging (through subsidies) the use of plugins that exert a preference to similar, safe and well-known delivery paths and/or delivery schedules, that lower traffic risk, spoilage, food defects and stress [4.3.2, 5.3.3].

Towards that end that considers the wellbeing and morale of the delivery agent, extra support can be provided by **customer co-creation** incentives with special plugins that will increase the involvement of the end-user [4.3.2, 4.3.3, 5.2.7]. This can be done by providing special perks, coupons, or governmental **subsidies** when customers use online payments (to reduce the need for change and minimize black economy), when they justifiably care for the movement restriction of the riders during bad weather conditions cancelling or postponing their orders once the system advices them so, or are willing to provide preset schedules for the meals a few hours sooner than the serving requirement, enabling the rating from the riders towards their clients, etc.

The end-user co-creation is important during times of crisis [4.3.3, 5.1.1] since it can allow for the supply chain to work in multiple speeds and prioritizing/expediting the procedures for products of rated emergency, with algorithms that regulate the geographic dispersion of service, dynamism, urgency and flexibility by managing "lazy" or "partial" commitment strategies, per case [5.1.1, 5.2.7].

## 6.3. Intrinsic mathematical properties – An algorithmic Approach

Another important point, similar to the **algorithmic despotism** that was described in previous paragraphs, is an **hegemonical issue** attributed to specific innate properties of the algorithmic nature, rather than imposed deliberately due to an external (human) **authoritative interest**. It was found that when a platform succeeds in dominating a market for some time then it starts becoming **'focal'** during the current period, or in other words, the dominant entity in history presents better chance (momentum) to dominate in the future [4.4.2] given the adoption rate and (delayed or not) **Network Effects** [5.3.2]. The argument is that any novel social welfare strategies may be defragmented and reduce in quality as more platforms become more forward looking (i.e. the planning is set in a **presbyopic manner**). The same can happen when **consumer heterogeneity** is increased, as the effects of focality are reduced and the competitive platforms are less inclined to insist for a future focal location. In other words, there needs to be an end-user base mass that will (actively or passively) support the novel fairness tactics for them to be included in the focal point (the standard) policies in the future, too – and this may require a regulated incentive attribution [5.1.1, 5.3.2]. This is the main reason that such acts need to be orchestrated by a commonly accepted figure of authority, like the governmental constitutions and robustly established by a broadly accepted database schema.

Additionally, some algorithms seem to produce **revenue inequalities** as they focus to optimize courier routes in places with high congestion probability, which occurs in areas of high urbanization, which is turn leads to high concentration of quality orders opportunities (multi-bundle, multiple destination ones). These types of algorithms try to extract the maximum possible sum of income, while **exerting a kind of greediness**, rendering the otherwise perfect algorithms the entities that create the inequitable income challenges on fellow-workers of the same fleet (let alone the ones belonging to some competitor) who may be unfortunate enough to be located in the suburbs or a few miles out of the city (or set district) limits [4.4.3]. The **monopolistic** behavior that emerges from such algorithms tends to help the few fortunate drivers who are close to multiple opportunities, intensifying their privileged position and subsequently encouraging their **self-interest** which is paid by acquiring or holding these positions in the future, too [4.4.4, 5.3.3, 5.3.4]. Similar aggressive designs use the JIT concept to exploit any savings that arise from large-scale orders by batching [5.1.2] and minimizing the FM and LM waiting times

[5.3.3]. This is a good idea that keeps the involved customer's and driver's experience high, but still encourages the revenue inequality [4.4.5].

The suggestion in such cases is the inclusion of plugins which will be able to **parametrically reshape the objectives** of the algorithms (given that the algorithms **provision for the fairness dimension**) to consider increasing or decreasing cooperativeness (with inter-communicating agents from distant areas) [5.2.4] and by using **selective projection of the distinctive order opportunities** per agent located in the city centers, to compensate for the fortunate positioning against the rest. The plugin may then conduct regular **sensitivity analysis as a feedback to check the influence of the platform's geographical reach and total revenues against its leverage to total fairness** (like the Gini coefficient).

In order to regulate the proper and legitimate use of the software plugins described, there need to exist a number of benchmarks that will be able to capture a well-rounded view of the algorithm's behavior. This will also ensure that the algorithms are best fitted to aid the model under examination, since, as already stated, there may exist intrinsic behavior in the mathematical approaches that are not necessarily fit for purpose or that selectively honor the nature of the constructed model, under special circumstances. In other words, **the benchmarks will audit and guarantee** that the tools dedicated to increase social welfare are **operating as expected** and are **parameterized properly** and include the constraints that **realistically characterize** the properties of the field of application [4.4.6].

Finally, a good counter-measure of congestion (concertation) trends is the inclusion of payoff policies, which can be included and audited as well, in the same software described above. Such policies can be applied to lower traffic risks but also maximize the long-term profits of all platforms by avoiding bottle necks in the routing paths. The idea for balancing out such trends (like the ones that also create inequality) is to make the riders perceive the alternative route suggestion as worthy i.e. to incentivize their contribution of selecting the non-congesting route by accompanying payoffs. The compensating awards will be designed to be valued as high as needed (with a calculation facilitated through a Q-learning based algorithm for example), in order for the individualistic vehicles to value the decision of an alternate route selection as worthy. This, in turn, increases fairness and improves the efficiency of the system. The software can self-regulate the dynamic response of its routing optimization technique, by injecting incentives only when required in order to balance the **locality of controlled fairness**. This is why the payoff needs to be managed to cost no more than the sum of the negative effects (like traffic jams, accidents, conflict of commercial interests, order cancellation due to tighter time-windows, fuel consumption, pollution, that a greedy system produces when no regulation is applied), or the platforms will once again reach a suboptimal equilibrium [4.4.7].

From a managerial point of view, the firms, need to take advantage of the group dynamics of social learning [4.1.2] through marketing campaigns to allow for their customer base and potential customers to infer and/or control the popularity of the aiming (fairness) practices of the firm (through common perception). This means that the private business self-regulation needs to be deliberately aligned with the governmental regulations and committed, as instructed by [3.5] in order to promote this strategy on its favor. The adoption of such practices will have a number of benefits:

a) **branding:** first and foremost, it will create a fair and rightful standard for the company and most importantly it will contribute towards that end for the whole industry, gradually transforming to an iconic trusted brand [3.4.5]

b) **operations:** any short-ended sacrifice will yield fruitful results in the future demands of the public, improving the working conditions for the delivery agents which in turn improve the quality of end-user service and subsequently, the firm's popularity, capitalizing on the consumer's OFDAs ratings [3.4.6]

c) **marketing:** any policies that motivate meritocracy, transparency, accountability, platform cooperation, full-time contracts, social welfare, various personal perks and insurance, promote the firm's credibility on *Corporate Social Responsibility* (CSR), improving its brand identity that strengthen its market position [3.4.4, 3.4.6].

d) **logistics:** in turn, a strong market position will further lower costs due to coordinated dynamic pricing and lower inventory control [3.1.1, 3.1.2, 3.1.4, 3.2.5]. This is a step closer to a platform design that favors inter-fleet co-operation and transparency, encourages the new offerings brought by extra food-cooperatives [3.6.3, 5.2.1], improves the timely order response, reduces the FM and LM challenges [4.3.2, 5.3.3] and, in part, tackles demand uncertainty [3.1.3, 3.6.2].

e) **diplomacy:** adopting principles applied in the net-politic science theory, an early law conformity will place the firm in a strong argumentative position for future government negotiations regarding legal shaping and enforcement

f) **contingency planning:** from an early law conformity will guarantee the reduction of any compliance future risks

g) **active/passive tacticianism:** early law conformity can be viewed as a strategic investment as it constitutes a potential redemption threat against any unlawful competitors, in the future.

Additionally, it is worth mentioning that this new position of the firm (that supports the fairness among its fleet members) is stable in terms of maintenance, given that it communicates its principles through a well-designed and easy to use interface, that ensures its publicly perceived value which translates into customer retention, loyalty [3.3.1, 3.3.2, 3.3.3, 3.4.1, 3.4.2, 3.4.3] and stronger network effects [5.3.2].

If anything, the recent events of Covid-19 stressed the importance of provisioning for robust solutions especially in the industry of delivering perishable goods/items. Due to the high complexity involved, the most promising methods are the ones comprised of **evolutionary algorithms** which will heuristically **adapt to the quick changes of the any ecosystem** [5.1.4]. This primarily can be done by including the riders' input more actively in the algorithmic loop, enhancing their feedback to the platform and valuing their perspective, thus developing an extra sense for prioritizing the various objectives [3.2.1, 3.2.2, 3.2.3]. This can strengthen the algorithmic operation as far as it concerns the mid-term profit and log-term fairness, by allowing a 2-stage solution [3.2.4, 5.1.4]. The 1st stage may value issues of immediate interest like congestion incidents and parking availability working to primarily optimize for profit, in a shorter planning horizon. The 2nd stage may apply compensatory directions based on both historic data and forecasting [3.6.2] like the inclusion of peak-times, to apply proper rider-order matching, scheduling, dispatching and bundles that favor each rider), primarily optimizing for fairness, in a wider planning horizon [4.4.2, 5.2.6, 5.3.1, 5.3.4].

A credible position that honors the respective SLAs can be further strengthened to a point where it may encourage expansion of the fleet (testing the scalability of the firm) by the introduction of heterogeneous, crowd sourced, fleet [3.1.6, 3.1.7, 5.1.3, 5.3.3]. Such an aspiring entrepreneurial move, requires some pivoting, and it is questionable [3.6.3] if there is any DSS fit for the purpose [4.4.6].

On a similar note it will be worth investigating the inclusion of offerings of joint storage, further expanding the collaborative activities through the established governmental framework (which will include **new legal and regulative settings for the matter)**. The only skepticism is involved around the social aspects of the matter, like the **individualistic will to support such activities**, the **group-dynamics in the decision-making political set** and the **interdependencies of interests of various stakeholders**.

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