

# A GRASP algorithm for the concrete delivery problem.

Ousmane Ali<sup>(1)</sup>, Jean-François Côté<sup>(2)</sup>, Leandro C. Coelho<sup>(3)</sup>

(1) `nassoma-wattara-ousmane.ali.1@ulaval.ca`

(2) `Jean-Francois.Cote@fsa.ulaval.ca`

(3) `Leandro.Coelho@fsa.ulaval.ca`

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## Abstract

The concrete delivery problem (CDP) is a combinatorial optimization problem that involves scheduling the delivery of ready-mixed concrete to construction sites while balancing the conflicting goals of minimizing transportation costs and maximizing customer satisfaction. This paper proposes an exact formulation and a heuristic approach based on the Greedy Randomized Adaptive Search Procedure (GRASP) to tackle a new variant of the CDP that incorporates realistic side constraints, such as drivers' working shifts, minimum working time for each driver, and overtime penalties. Additionally, the problem also considers the possibility of customers requiring multiple types of concrete to be delivered within the same time window. The performance of the proposed heuristic is evaluated on real-world and generated CDP instances, and it is compared to another variant to demonstrate its effectiveness.

**Keywords:** Vehicle scheduling; concrete delivery; GRASP; ready-mixed concrete

## 1 Introduction

Concrete is a widely used building material in construction projects. ~~It is a perishable product that can be affected by many different factors that impact its quality [Sinha et al., 2021], which is crucial for the durability and strength of the final construction.~~ *Its nature is*

Concrete comes in two types: ready-mixed concrete (RMC) and site-mixed concrete (SMC). RMC is manufactured in a batch plant and delivered to the construction site, while SMC is produced on-site using raw materials stored on the construction site. ~~Site-mixed concrete can avoid delays caused by road traffic, but it has a slower and more difficult production process, requires storage for mixing materials and equipment, and is suitable for low amounts of concrete. On the other hand, RMC has better quality and benefits from lower production costs [Muresan, 2019]. However, to take advantage of these benefits, the batch plant manager must ensure efficient and prompt delivery on the construction site, which may require a fleet of high-cost revolving drum trucks (concrete mixers) to dispatch the ready-mixed concrete.~~ *Using SMC*

Concrete delivery under the form of RMC is subject to many operational constraints that make it a challenging problem met in Operations Research and addressed by the Concrete Delivery Problem (CDP). In this paper, we study a variant of the Concrete Delivery Problem to schedule the daily production and dispatching of RMC for a company located in the province of Quebec, Canada. This company operates multiple batching plants with varying production rates, using a fleet of concrete mixers with different capacities. Each plant has

its own fleet of trucks. <sup>under certain conditions,</sup> however, the trucks <sup>can</sup> ~~are able to~~ move between plants if necessary. The trucks must return to their home plant at the end of the day. The company owns two types of trucks with different capacities ~~but also has the option to~~ call on an external fleet when needed. They serve construction sites from any of their ~~batch~~ plants, with the first delivery starting at the time specified by the customer. The loading and unloading of a concrete mixer depend on the truck capacity, the loading rate at the plant, and the unloading rate at the construction site. Drivers are allocated based on their daily work schedules. A customer may request several types of concrete to be delivered within the same time window, with no required sequence for the orders, but an order can only start after the completion of the previous order. This constraint generalizes the linked order constraints of Durbin and Hoffman [2008] where some customers place two orders for the same day and request that they are linked (the second order begins only after the first order is completed). The setting of ~~this~~ <sup>own</sup> study is similar to a variant of the ~~Concrete Delivery Problem~~ <sup>CDP</sup> previously studied in Schmid et al. [2009, 2010]. However, ~~it~~ <sup>we</sup> includes the plant's production rate and driver shift schedule, ~~and does not consider unloading instrumentation in contrast to the previous research.~~ The company uses a centralized dispatcher system to schedule all daily orders, but this system has issues satisfying all daily demands without using an external fleet.

According to Blazewicz et al. [2019], the ~~concrete delivery problem~~ <sup>CDP</sup> combines vehicle routing with scheduling issues to plan routes to deliver concrete from batch plants (depots) to customers' construction sites. ~~Ready-mixed concrete~~ <sup>RMC</sup> is an on-demand product with a short life cycle from production through end use. It cannot be stored and cannot stay too long ~~in~~ <sup>on</sup> a truck, or it will harden. Hence, concrete mixers must deliver RMC at the planned construction site shortly after its production. ~~RMC production and delivery is described~~ <sup>describes</sup> Tommelein and Li [1999] as an example of a Just-In-Time (JIT) production system in construction. A customer quantity requirement is often greater than the truck size and must be fulfilled by multiple deliveries. In that sense, CDP is ~~like~~ <sup>similar to</sup> the Vehicle Routing Problem (VRP) with split delivery (VRPSD) [Archetti and Speranza, 2008], except that the same truck may visit a customer more than once. Concrete hardens quickly, so ~~when there are multiple deliveries, they~~ must be done back-to-back or at least close in time to avoid the problem of cold joint, which can reduce the strength and durability of the concrete. Customers request to be served within a specific time window, which can complicate truck-loading schedules when a plant can only load one truck at a time. Similarly, only one truck can unload at a time at a customer location, sometimes leading to concrete mixers queuing and waiting their turn to deliver. Furthermore, with trucks of varied sizes, loading, travel, and unloading times that may be uncertain, the ~~Concrete Delivery Problem~~ <sup>CDP</sup> is a complex ~~problem to solve and has been proven to be NP hard~~ <sup>and challenging</sup> [Asbach et al., 2009, Kinable et al., 2014].

In this paper, we propose a mathematical model and a Greedy Randomized Search Procedure (GRASP) heuristic solution to solve a new variant ~~of~~ the CDP. Our model takes into consideration the working shifts of the drivers and the scheduling of multiple orders within the same time window at a construction site. To the best of our knowledge, this paper is the first that deals with these specific constraints in the context of the CDP.

The rest of the paper is structured as follows: Section 2 provides a literature review of previous work related to the CDP. Section 3 provides a formal description and mathematical model of the problem. In Section 4, we describe the ~~Greedy Randomized Search Procedure~~ <sup>GRASP</sup> algorithm and the constructive heuristics developed to solve this variant of the CDP. Section 5 presents computational experiments to evaluate the proposed approach, and finally, the conclusions are presented in Section 6.

## 2 Literature review

A text mining approach by Maghrebi et al. [2015] for reviewing the ready-mixed concrete literature showed that concrete technology and material science are the main core of research in this area. Academic research on concrete batching and delivery began in the late 1990s. Tommelein and Li [1999] described ready-mixed concrete (RMC) as a prototypical example of a Just-In-Time production system in construction and identified two practices for delivering it. One approach is for the customer to haul the product from the batch plant with their concrete mixer, while the other approach is for the batch plant to deliver the concrete directly to the customer's location. This latter approach is the one that has been studied in all related papers found in the literature.

Several works to schedule and dispatch concrete production and delivery have mainly focused on simulation-related methods. These methods can be standalone, such as those used by Zayed and Halpin [2001], Wang et al. [2001], Tian et al. [2010], Panas and Pantouvakis [2013] and Galić and Kraus [2016], among others. Alternatively, these methods can be hybridized with optimization techniques, such as those used by Feng et al. [2004], Lu and Lam [2005], Feng and Wu [2006], etc. Wang et al. [2001] developed a simulation model to reveal the effect and value of the concrete mixers' inter-arrival time on the productivity of hired unloading equipment on site. Feng et al. [2004] used a combination of Genetic Algorithm (GA) and simulation process to minimize the total waiting time for trucks at a customer site. The study focused on loading trucks with identical capacities at the same batch plant, with fixed loading and unloading durations. The GA was used to find the best loading sequence of RMC trucks to be assigned to different construction sites. The simulation process determined the loading, arrival, departure, and waiting time of trucks and thus evaluated the cost of each dispatching sequence. They evaluated their method using data from a batch plant in Taiwan with up to nine customers served. Mayteekriangkrai and Wongthatsanekorn [2015] addressed the same problem with the same data using a bee algorithm (BA) and found better solutions than the GA. Lu and Lam [2005] used the same combination of GA and simulation to determine the optimal number of concrete mixers to be deployed and an optimal schedule for batching and delivering concrete. Their objective was to minimize the idle time of the site crew due to late concrete deliveries and truck queuing time. In this setting, it was also necessary to deliver a batch of mortar on-site to lubricate the unloading pump before the concrete delivery. As such, the simulation model also included the batching and delivery of mortar. Finding the best RMC truck size was also the purpose of the discrete-event simulation model proposed by Panas and Pantouvakis [2013].

In addition to simulation-based methods, several other approaches have been used in the literature to solve the CDP. These include metaheuristics [Faria et al., 2006, Misir et al., 2011, Maghrebi et al., 2016b, Yang et al., 2022], exact methods [Yan and Lai, 2007, Asbach et al., 2009, Kinable et al., 2014], matheuristics [Schmid et al., 2009, 2010], Benders Decomposition [Maghrebi et al., 2014a], Column Generation (CG) [Maghrebi et al., 2014b, 2016a], Lagrangian relaxation [Narayanan et al., 2015], and machine learning approaches such as those used by Graham et al. [2006], Maghrebi and Waller [2014], Maghrebi et al. [2016c]. Matsatsinis [2004] designed a decision support system (DSS) for the dynamic routing of both concrete and pumps that may be necessary for some construction sites to aid in the unloading of concrete. The DSS considered the availability of three plants but stipulated that vehicles fulfilling the same order must all load at the same plant. Orders that could not be executed immediately could be postponed for the next day. The routing of the pumps was modelled as a multi-depot vehicle routing problem with time windows. Naso et al. [2007] proposed a sequential GA method combined with constructive heuristics to solve an-

134 other variant of the CDP. In this problem, the plant's production schedule must account for  
 135 orders for concrete to be delivered to a customer site and orders that customers must pick  
 136 up themselves. The algorithm first schedules the plant loading operations before scheduling  
 137 truck deliveries. The authors also developed a non-linear model that minimizes transporta-  
 138 tion costs, waiting times, outsourced costs, and overtime work. They ran experiments using  
 139 real-world instances of a concrete supply chain in the Netherlands and found a reduction in  
 140 the number of requests, ~~redirected to external companies~~. Yan and Lai [2007] also considered  
 141 overtime considerations in their paper, which focused on scheduling RMC for one batching  
 142 plant with two loading docks. The study took into account that overtime wages are paid  
 143 for factory and construction site operations after 4 PM. They developed a mixed-integer  
 144 programming (MIP) model on a time-space network to minimize travel times and operating  
 145 costs at both normal and overtime working hours at the plant and the construction sites.  
 146 They tested the model using real data consisting of ~~3~~ <sup>thru</sup> days of operation using a two-stage  
 147 algorithm. First, they solved the MIP relaxation with CPLEX. Then, they simplified the  
 148 original model by fixing some decision variables before solving it. The algorithm was found  
 149 to improve the actual plant operation by 10%. A time-space network is the key component  
 150 of the real-time ~~decision support system (DSS)~~ developed by Durbin and Hoffman [2008] to  
 151 solve a dynamic CDP ~~problem~~ every five minutes. The DSS is able to receive new orders,  
 152 schedule them on the fly, and handle unexpected events such as plant closures, truck break-  
 153 downs, and delays in transportation times. The authors combined the DSS with a ~~Tabu~~  
 154 ~~Search (TS)~~ heuristic to warm start CPLEX, which made the model performant enough to  
 155 solve instances with up to 1,500 loads per day with up to 250 trucks. The DSS also considers  
 156 the case of a customer who places two orders, with the first being completed before the sec-  
 157 ond starts. Further insights on the real-time planning and monitoring of CDP are available  
 158 in Garza Cavazos [2021]. Another variant of the CDP is modeled by Schmid et al. [2009] as  
 159 an integer multicommodity network flow (MCNF) problem on a time-space network. In this  
 160 paper, concrete is delivered using a heterogeneous fleet of vehicles, and each plant can load  
 161 an unlimited number of trucks simultaneously. Some of the trucks have specialized equip-  
 162 ment and must arrive first at certain construction sites to assist in unloading the concrete.  
 163 The objective is to fulfill all orders, minimize the travel cost, and avoid delays between  
 164 two consecutive unloading operations for an order. The model is typically solved using  
 165 a matheuristic algorithm that combines the MCNF with a variable neighborhood search  
 166 (VNS) heuristic. The method can quickly solve large problem instances with more than 60  
 167 orders per day without encountering any memory issues. The same problem is addressed  
 168 by Schmid et al. [2010] who proposed a ~~mixed integer programming (MIP)~~ model combined  
 169 with a VNS and a very large neighborhood search (VLNS) to develop two matheuristics  
 170 approaches. Comparisons between both matheuristics and a standalone VNS show that the  
 171 former methods are much better and suitable for solving larger problem instances. These  
 172 methods also provide better solutions for small to medium instances than the matheuristic  
 173 used in Schmid et al. [2009]. A pure VNS approach with the same problem but without the  
 174 use of instrumentation has been applied by Payr and Schmid [2009].

175 Regarding objectives, most authors have focused on minimizing travel time and delays  
 176 between consecutive deliveries. However, some authors have been more interested in max-  
 177 imizing customer satisfaction alone. We find these situations in the works of Durbin and  
 178 Hoffman [2008], Kinable et al. [2014], Kinable and Trick [2014], Sulaman et al. [2017]. Kin-  
 179 able et al. [2014] introduce a general MIP and constraint programming (CP) models of the  
 180 CDP reflecting the main constraints commonly found in all CDP works: time lag and no  
 181 overlapping between consecutive deliveries, covering of all customers' demands, delivery time  
 182 window, and heterogeneous fleet. However, the model did not include constraints limiting

the time that concrete may reside in a truck. The authors propose a constructive heuristic that schedules the visits to the customers one by one according to the start time of the visit and the truck capacity. The procedure is invoked multiple times for different permutations of the customer's order which is determined using the steepest descent (SD) local search procedure. One of the paper's main contributions is the creation of the first public test instances for the CDP with up to 50 customers, four batching plants, and 20 concrete mixers. They found the CP model to be highly effective in finding high-quality solutions in relatively ~~little~~ <sup>short</sup> time or improving existing schedules, while the MIP model can be used to compute bounds, as it seems ineffective in solving large problem instances. Finally, the heuristic often yields good solutions in less than a second. A detailed analysis of the MIP model presented in ~~citekinable2014concrete~~ and of two more compact models can be found in the thesis of Hernández López [2020]. In Kinable and Trick [2014], we found an attempt to solve the previous problem with a Logic-based Benders' approach. Sulaman et al. [2017] expand upon the SD heuristic proposed in Kinable et al. [2014], proposing a Simulated Annealing (SA) with a Time-Slot Heuristic (TH). TH mechanism is to look for a slot between existing visits of a truck to schedule a new delivery instead of assigning it to the time slot strictly after the truck's latest assigned delivery. The goal is to reduce the large time gaps that can be present in a schedule created with SD due to ignoring the intermediate available time slots. Experimental results indicated that ~~the~~ TH outperforms SD in speed and solution quality. A generalization of the MIP model of Kinable et al. [2014] is addressed in Asbach et al. [2009]. This model simultaneously minimizes the total sum of travel costs and the penalty costs for customers with unfulfilled demand. A customer can request that all concrete deliveries come from the same plant or a subset of plants and that a delivery truck belongs to a subset of the vehicle fleet. The MIP model is used in a local search scheme as a black-box solver to reoptimize an incumbent solution in which a neighborhood operator has unfixed some variables. Tzanetos and Blondin [2023] provide an overview of the various methods used in the literature to address the Concrete Delivery Problem and categorize the problem formulations based on the different concepts used in the literature, such as Integer Programming (IP), time-space network, and job-shop model. They also discussed the consistency between industry needs and existing constraints and provided insights into the datasets corresponding to real-world cases, identifying the necessary data for practitioners.

### 3 Problem description

The focus of this paper is the distribution of ~~ready-mixed concrete~~ <sup>RMC</sup> from a Canadian company that operates in the greater Montreal area. When a customer places an order, it is received at a central center and ~~then~~ assigned to one of the company's batching plants. These plants produce the concrete and ~~then~~ deliver it to the customer. The problem we are examining involves a set of batching plants, a set of customer orders, and a set of concrete-mixer drivers.

The company owns a total of eight batching plants, located in various geographical regions. Each plant has a loading bay that can only accommodate one truck at a time, which leads to trucks lining up. Let  $\mathcal{B}$  be the set of batching plants. The plants are heterogeneous, as each plant has its own hourly loading rate, represented by  $\tau_b^l$ , which affects the duration of the loading process. After the concrete <sup>loading</sup> ~~has been loaded~~, the driver spends  $\alpha_b$  minutes adjusting the concrete in the truck before heading to the customer site. A batching plant can serve a construction site as long as the travel time between the two is less than the concrete's lifespan, which is represented by  $\Delta$ . Each plant has its own assigned fleet of trucks, but it can ~~also~~ borrow trucks from other plants or hire external <sup>vehicles</sup> ~~fleets~~ if necessary.



230 A customer  $i$  requests a total of  $q_i$  of one or several types of concrete to be delivered  
 231 to his construction site on a particular day. We call an order a request for a specific type  
 232 of concrete. When placing an order  $o$ , ~~the~~ customer  $i$  specifies the required quantity,  $q_o$ ,  
 233 the desired arrival time of the first concrete mixer,  $a_i$ , and the unloading rate at their  
 234 construction site,  $\tau_i^u$ . If the order requires more concrete than a single truck can carry,  
 235 multiple deliveries are scheduled. Let  $O_i$  be the ~~unsorted~~ <sup>unsorted</sup> set of all orders requested by  
 236 customer  $i$ . Each element of  $O_i$  must be thoroughly delivered before moving ~~to~~ <sup>to</sup> another  
 237 order. One element  $o$  of  $O_i$  must have its first delivery start at  $a_i$ , while the others can  
 238 start any time after all deliveries of  $o$ . Once a plant is chosen to produce a customer's first  
 239 delivery, it must be the provider of all subsequent deliveries of this customer. To prevent cold  
 240 joint issues with the concrete, subsequent deliveries must be made ~~just in time, or at least~~ <sup>in close succession.</sup>  
 241 ~~close in time~~. We define a maximum time lag  $\gamma_i$  beyond which no next unloading operation  
 242 should be allowed. The construction site unloading rate and the quantity to unload give the  
 243 time necessary to discharge a truckload.  ~~$\mathcal{C}$  is the set of construction sites (customers) with~~  
 244 a planned delivery for the day,  ~~$\mathcal{O}$  is the set of all requested orders.~~

245 The company has two types of concrete mixer trucks with capacities of 8 and 12 cubic  
 246 meters. Each driver  $k$  is assigned to a specific batching plant and is responsible for driving  
 247 a truck with a specific capacity  $Q_k$ . The set of drivers is represented by  $K = \cup_{b \in \mathcal{B}} K_b$ ,  $K_b$   
 248 being the set of drivers scheduled to start their shift at ~~the~~ <sup>at</sup> batching plant  $b$ .  $t_{ij}$  is the known  
 249 time to travel between any two locations  $i$  and  $j$ . A scheduled driver  $k$  is required to begin  
 250 their shift at  $H_k$ , work for a minimum of  $M_T$  hours and a maximum of  $N_T$  hours during  
 251 regular working hours, with the possibility of overtime of up to  $O_T$  hours.

252 A driver typically loads RMC at their assigned batching plant, but may ~~also~~ <sup>be</sup> required  
 253 to drive to and load at other plants if needed. Batching plant produces concrete on-demand  
 254 with recipes specific to each customer. This means that a truck ~~cannot hold orders for more~~ <sup>can only transport</sup>  
 255 ~~than~~ one customer, even if there is spare capacity. To fulfill multiple orders, a driver must  
 256 refill at a plant between deliveries. After unloading the RMC, a driver takes  $\beta_k$  minutes to  
 257 clean the concrete mixer before travelling to ~~his next~~ <sup>the next</sup> loading plant.

258 A solution to the problem involves making decisions about truck loading schedules, driver  
 259 assignments to different deliveries, and truck arrival times at construction sites for unloading.  
 260 For a batching plant, the decision involves choosing which driver to load, when to load  
 261 them, and which construction site they should deliver to. For a driver, the decision involves  
 262 determining the sequence of loading depots and delivery sites. And for a construction site,  
 263 the decision involves determining the arrival times of all scheduled deliveries for the day.

264 We now present a formal definition of our problem. Let  $n_o$  be the number of deliveries  
 265 needed to fulfill order  $o$ .  $n_o$  is not known in advance, as we use a fleet of trucks with various  
 266 capacities. However, we can compute its lower ( $n_o^{\min}$ ) and upper ( $n_o^{\max}$ ) bounds using the  
 267 capacities of the highest ( $Q_{\max}$ ) and smallest ( $Q_{\min}$ ) available trucks. The lower bound is  
 268 the number of deliveries needed if we only use trucks of capacity  $Q_{\max}$ , while the upper  
 269 bound is the number of deliveries needed if we only use trucks of capacity  $Q_{\min}$ .

$$\left\lceil \frac{q_o}{Q_{\max}} \right\rceil \leq n_o \leq \left\lceil \frac{q_o}{Q_{\min}} \right\rceil \quad \forall o \in \mathcal{O}. \quad (1)$$

270 Let  $d_o^j$  be the  $j_{th}$  visit with load  $q_o^j$  for order  $o$ . We represent the delivery of order  $o$  by  
 271 the visits to the ordered set of nodes  $\mathcal{D}_o = (d_o^0, d_o^1, \dots, d_o^{n_o})$ . We represent the deliveries  
 272 of customer  $i$  by the ordered set  $\mathcal{D}_i = (\mathcal{D}_{o_1}, \mathcal{D}_{o_2}, \dots, \mathcal{D}_{o_{|O_i|}})$ , where  $o_r$  is the  $r_{th}$  order  
 273 delivered. We will refer to  $d \in \mathcal{D}_i$  ( $d \in \mathcal{D}_o$ ) as the  $d_{th}$  potential delivery of customer  $i$  (order  
 274  $o$ ).  $\mathcal{D} = \bigcup_{i \in \mathcal{C}} \mathcal{D}_i$  is the union of all delivery nodes.

275 We represent each plant  $b$  by the ordered set  $L_b = \{L_{b,1}, L_{b,2}, \dots, L_{b,n(b)}\}$  of loading  
 276 docks nodes, with  $n(b)$  being the number of delivery nodes at a maximal travel time of  $\Delta$  of  
 277  $b$ . We will refer to  $L_{b,l}$  or  $l \in L_b$  as the  $l$ th potential loading operation at  $b$ .  $\mathcal{L} = \bigcup_{b \in B} L_b$   
 278 is the union of all loading docks.

279 Each driver leaves and returns to his home plant each day. We represent a driver  $k$  home  
 280 plant's with a starting  $s_k$  and ending  $e_k$  depot.  $S$  and  $E$  are respectively the sets of starting  
 281 and ending depot.

282 We define our problem on a complete directed graph where  $V = \{S \cup \mathcal{L} \cup \mathcal{D} \cup E\}$  is the  
 283 set of nodes. The arc sets are  $A = \{(i, j, k) \mid i, j \in V, k \in K\}$ , and  $A^D = \{(i, j) \mid i, j \in \mathcal{D}\}$ .  
 284  $A$  corresponds to allowed movements of drivers from node  $i$  to node  $j$ . For each driver  $k$ ,  
 285 the allowed movements are the following:

- 286 • From the starting depot  $s_k$  to a loading dock  $l \in \mathcal{L}$  or to the ending depot  $e_k$ .
- 287 • From a loading dock  $l \in \mathcal{L}$  to a delivery node  $d \in \mathcal{D}$ .
- 288 • From a delivery node  $d \in \mathcal{D}$  to a loading dock  $l \in \mathcal{L}$  or to the ending depot  $e_k$ .

289 For a customer  $c$ , arcs in  $A^D$  link consecutive delivery nodes of the same order  $\{(i, j) \in$   
 290  $\mathcal{D}_o, o \in \mathcal{O}_c, i < j\}$ , and pair of delivery nodes of two different orders  $\{(i, d_{o_2}^0), i \in \mathcal{D}_{o_1}, i \geq$   
 291  $n_{o_1}^{min}, o_1, o_2 \in \mathcal{O}_c, o_1 \neq o_2\}$ .

292  $\delta^+(i) = \{(i, j, k) \in A\}$ , and  $\delta^-(i) = \{(j, i, k) \in A\}$  are the outcoming and incoming arc  
 293 sets of any node  $i \in V$ . Similarly,  $\delta_D^+(i) = \{(i, j) \in A^D\}$ , and  $\delta_D^-(i) = \{(j, i) \in A^D\}$  are the  
 294 outcoming and incoming arc sets of delivery node  $i \in \mathcal{D}$ .

295 Let the binary variable  $x_{ij}^k$  be 1 if driver  $k$  travels from node  $i$  to  $j$ . Binary variable  
 296  $y_i$  equals 1 if customer  $i$  is completely served.  $v_i$  is the start of the loading (unloading)  
 297 operation at node  $i \in L \cup D$ .  $w_i$  is the end of the loading (unloading) operation at node  
 298  $i \in L \cup D$ . Binary variable  $u_{i,j}$  equals 1 if delivery node  $j$  is served just after delivery  $i$ .  
 299 Binary variable  $\sigma_{ib}$  equals 1 if customer  $i$  orders' are loaded from plant  $b$ .

300 A driver  $k$  leaves his starting node exactly once a day and travels to either a loading  
 301 dock or his ending node. When loading at a loading dock  $i$ , he takes some time to adjust the  
 302 concrete in the truck before travelling to delivery node  $j$  to unload. The loading operation  
 303 duration depends on the plant loading rate and the quantity  $q_j^k$  of RMC to load towards  $j$ .  
 304 After completing his last unloading operation of the day, he returns to his end node.

$$\sum_{j \in \delta^+(s_k)} x_{s_k j}^k = 1 \quad \forall k \in K \quad (2)$$

$$v_j \geq w_i + \alpha_i + t_{ij} - M(1 - x_{ij}^k) \quad \forall i \in \mathcal{L}, j \in \mathcal{D}, k \in K \quad (3)$$

$$w_i \geq v_i + \frac{q_j^k}{\tau_b^l} - M(1 - x_{ij}^k) \quad \forall b \in \mathcal{B}, i \in L_b, j \in \mathcal{D}, k \in K \quad (4)$$

$$\sum_{j \in \delta^-(e_k)} x_{j e_k}^k = 1 \quad \forall k \in K \quad (5)$$

305 Constraints (4) ensure that two trucks cannot be loaded at the same time in a plant.

$$w_{l-1} \leq v_l \quad \forall b \in \mathcal{B}, l \in L_b, l \geq 1 \quad (6)$$

306 After completing a delivery at node  $i$ , a driver must clean the truck, and travel to the  
 307 next loading depot or end node. The unloading service depends on the construction site's  
 308 rate and the received quantity.

$$v_j \geq w_i + \beta_k + t_{ij} - M(1 - x_{ij}^k) \quad \forall i \in \mathcal{D}, j \in \mathcal{L} \cup \{e_k\}, k \in K \quad (7)$$

$$w_j \geq v_j + \frac{q_j^k}{\tau_c^u} - M(1 - x_{ij}^k) \quad \forall c \in \mathcal{C}, j \in \mathcal{D}_c, i \in \mathcal{L}, k \in K \quad (8)$$

309 The first service of any customer  $i$  has to start at the due time  $a_i$ . Let  $g_i$  be the gap  
 310 between the due time and the start of first service at  $i$ . This first service may be performed  
 311 at the first delivery node of any order  $\in \mathcal{O}_i$ . Constraints (11–13) are used to find the delivery  
 312 sequence of the first delivery node of all orders  $\in \mathcal{O}_i$ .

$$v_{d_o^0} \geq a_i \quad \forall i \in \mathcal{C}, \forall o \in \mathcal{O}_i \quad (9)$$

$$g_i \geq v_d - a_i - M \left( \sum_{j \in \delta_D^-(d)} u_{j,d} \right) \quad \forall i \in \mathcal{C}, \forall o_1 \in \mathcal{O}_i, d = d_{o_1}^0 \quad (10)$$

$$\sum_{o_1 \in \mathcal{O}_i} \sum_{j \in \delta_D^-(d_{o_1}^0)} u_{j,d_{o_1}^0} = |\mathcal{O}_i| - 1 \quad \forall i \in \mathcal{C}, |\mathcal{O}_i| > 1 \quad (11)$$

$$\sum_{o_1 \in \mathcal{O}_i} \sum_{j \in \delta_D^+(d_{o_1}^0)} u_{d_{o_1}^0,j} = |\mathcal{O}_i| - 1 \quad \forall i \in \mathcal{C}, |\mathcal{O}_i| > 1 \quad (12)$$

$$\sum_{j \in \delta_D^+(d_{o_1}^0)} u_{d_{o_1}^0,j} \leq 1, \sum_{j \in \delta_D^-(d_{o_1}^0)} u_{j,d_{o_1}^0} \leq 1, \sum_{j \in \delta_D^+(d_{o_1}^0)} u_{d_{o_1}^0,j} + \sum_{j \in \delta_D^-(d_{o_1}^0)} u_{j,d_{o_1}^0} \geq 1 \quad \forall i \in \mathcal{C}, \forall o_1 \in \mathcal{O}_i \quad (13)$$

313 For a customer, an order must be completed before starting another. Constraints (14–  
 314 15) enforce the precedence constraints between the last delivery of an order and the first  
 315 delivery of the subsequent order.

$$v_{d_{o_2}^0} \geq w_j - M(1 - u_{j,d_{o_2}^0}) \quad \forall i \in \mathcal{C}, \forall o_1, o_2 \in \mathcal{O}_i, j \in \mathcal{D}_{o_1}, (j, d_{o_2}^0) \in \delta_D^-(d_{o_2}^0) \quad (14)$$

$$v_{d_{o_2}^0} \leq w_j + \gamma_i + M(1 - u_{j,d_{o_2}^0}) \quad \forall i \in \mathcal{C}, \forall o_1, o_2 \in \mathcal{O}_i, j \in \mathcal{D}_{o_1}, (j, d_{o_2}^0) \in \delta_D^-(d_{o_2}^0) \quad (15)$$

316 Constraints (16–17) enforce the precedence constraints between two consecutive delivery  
 317 nodes of the same order.

$$u_{j-1,j} \geq u_{j,j+1} \quad \forall i \in \mathcal{C}, \forall o \in \mathcal{O}_i, j \in \mathcal{D}_o, 1 \leq j \leq n_o - 1 \quad (16)$$

$$u_{j-1,j} \geq \sum_{l \in \mathcal{L}} x_{lj} \quad \forall i \in \mathcal{C}, \forall o \in \mathcal{O}_i, j \in \mathcal{D}_o, j \geq 1 \quad (17)$$

318 Constraints (18–19) state that it is not possible for two trucks serving consecutive deliv-  
 319 eries to be unloaded at the same time and there is a maximum time lag between them.

$$v_j \geq w_{j-1} - M(1 - u_{j-1,j}) \quad \forall i \in \mathcal{C}, \forall o \in \mathcal{O}_i, j \in \mathcal{D}_o, j \geq 1 \quad (18)$$

$$v_j \leq w_{j-1} + \gamma_i + M(1 - u_{j-1,j}) \quad \forall i \in \mathcal{C}, \forall o \in \mathcal{O}_i, j \in \mathcal{D}_o, j \geq 1 \quad (19)$$

320 With constraints (20) and (21), we respectively impose that the cumulative capacity of  
 321 all concrete mixers serving an order and a customer may exceed the required quantities.



$$\sum_{d \in D_o} \sum_{k \in K} q^k \sum_{j \in \mathcal{L}} x_{jd}^k \geq q_o, \forall o \in \mathcal{O} \quad (20)$$

$$\sum_{d \in D_i} \sum_{k \in K} q^k \sum_{j \in \mathcal{L}} x_{jd}^k \geq q_i, \forall i \in \mathcal{C} \quad (21)$$

322 Constraints (22) and (23) impose that a loading or delivery node may only be visited  
323 once by one driver. Constraints (24) and (25) are degree constraints.

$$\sum_{k \in K} \sum_{j \in \mathcal{D}} x_{ij}^k \leq 1 \quad i \in \mathcal{L} \quad (22)$$

$$\sum_{k \in K} \sum_{i \in \mathcal{L}} x_{ij}^k \leq 1 \quad j \in \mathcal{D} \quad (23)$$

$$\sum_{k \in K} \sum_{i \in \mathcal{L}} x_{ij}^k = \sum_{k \in K} \sum_{i \in \mathcal{L}} x_{ji}^k \quad j \in \mathcal{D} \quad (24)$$

$$\sum_{k \in K} \sum_{i \in \mathcal{D}} x_{ij}^k = \sum_{k \in K} \sum_{i \in \mathcal{D}} x_{ji}^k \quad j \in \mathcal{L} \quad (25)$$

324 Constraints (26) and (27) impose that all orders of customer  $i$  must be loaded from the  
325 same plant.

$$\sum_{k \in K} \sum_{l \in \mathcal{L}_b} \sum_{d \in \mathcal{D}} x_{ld}^k \leq M * \sigma_{i,b} \quad \forall i \in \mathcal{C}, b \in \mathcal{B} \quad (26)$$

$$\sum_{b \in \mathcal{B}} \sigma_{i,b} \leq 1 \quad \forall i \in \mathcal{C}, b \in \mathcal{B} \quad (27)$$

326 Let  $w_k^1$  be the binary variables indicating if the driver  $k$  has reached the minimum number  
327 of hours worked in the day.  $w_k^2$  is a continuous variable indicating the gap between the driver  
328 working time and the normal working time.

$$M_T * w_k^1 \leq v_{e_k} - H_k \quad \forall k \in K \quad (28)$$

$$w_k^2 \geq (v_{e_k} - H_k) - N_T \quad \forall k \in K. \quad (29)$$

The objective function (30) minimizes the travelled distance, the penalty costs incurred when customers' demands are not fully satisfied, the lateness of each customer first delivery, the number of drivers who work under the minimum working time and the total overtime cost when drivers work beyond their scheduled hours.

$$\begin{aligned} \min \sum_{k \in K} \sum_{i \in \mathcal{L}} \sum_{j \in \delta^+(i)} t_{ij} x_{ij}^k &+ \sum_{k \in K} \sum_{i \in \mathcal{D}} \sum_{j \in \delta^+(i)} t_{ij} x_{ij}^k + \sum_{i \in \mathcal{C}} \beta_1 (1 - y_i) \\ &+ \beta_2 \sum_{i \in \mathcal{C}} g_i + \sum_{k \in K} \beta_3 * w_k^1 + \beta_4 * w_k^2 \end{aligned} \quad (30)$$

329 Let us consider the solution of a small instance of our problem illustrated in Figures 1 and  
330 2. Two batching plants  $B_1$  and  $B_2$  with three drivers serve two construction sites. Customer

331  $C_1$  requests one order of  $q_1^1 = 12 \text{ m}^3$ . Customer  $C_2$  requests three orders of  $q_2^1 = 3$ ,  $q_2^2 = 11$ ,  
 332 and  $q_2^3 = 1 \text{ m}^3$  of three different types of concrete.  $B_1$  has two drivers ( $D_1$ ,  $D_2$ ) using  
 333 concrete mixers of capacity  $8 \text{ m}^3$ , and  $B_2$  has  $D_3$  of capacity  $12 \text{ m}^3$ . Figure 1 depicts the  
 334 concrete mixers flow in the network. We schedule  $D_1$  and  $D_2$  to respectively deliver  $8$  and  
 335  $4 \text{ m}^3$  to  $C_1$ . We select  $o_2^2$  as the first order of  $C_2$  to deliver.  $D_3$  travels to  $B_1$  to load  $q_2^2$ ,  
 336 then visits  $C_2$  before returning to his home plant. Meanwhile, after their first trip,  $D_1$  and  
 337  $D_2$  deliver the remaining orders of  $C_2$ .

338 Figure 2 shows the sequence of loading and unloading operations. The first deliveries of  
 339  $C_1$  and  $C_2$  are timely and there is no gap between the two deliveries received by  $C_1$ . There  
 340 is a delay between the end of the first delivery and the start of the second delivery of  $C_2$ ,  
 341 however, it is less than the maximal time lag of 20 minutes defined for this example.

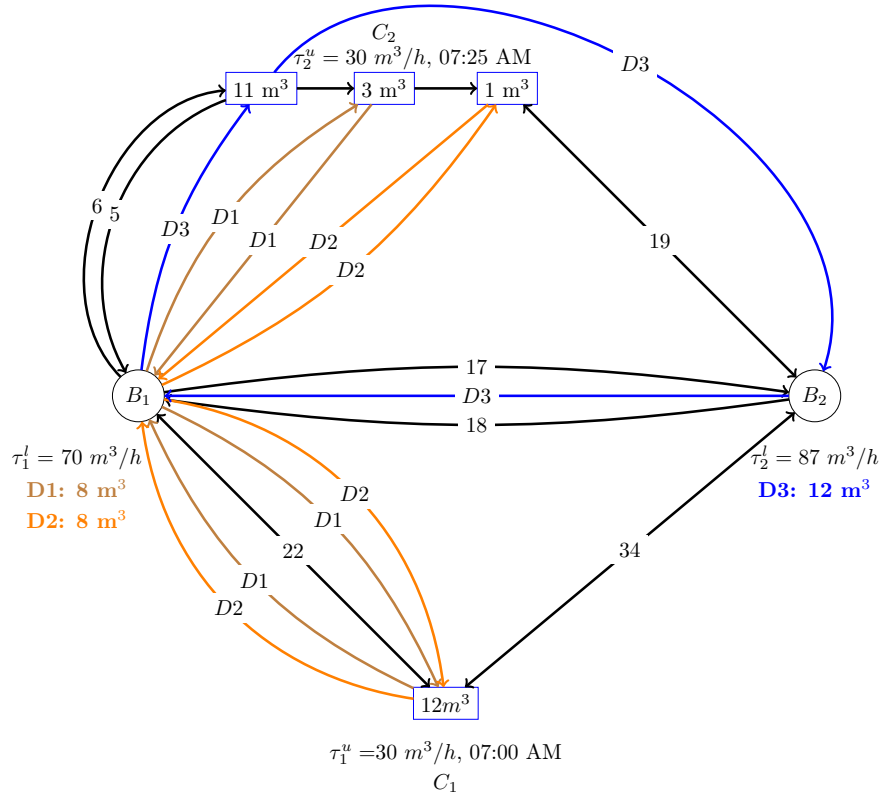


Figure 1: Solution of an instance with two plants, two construction sites, four orders, and three drivers.

## 342 4 Constructive heuristics and GRASP

343 We now present the heuristic approach we implement to solve this variant of the Concrete  
 344 Delivery Problem. Our method consists in constructing feasible solutions for the CDP  
 345 with randomized heuristics and iteratively calling these heuristics in the greedy randomized  
 346 adaptive search procedure (GRASP) metaheuristic.

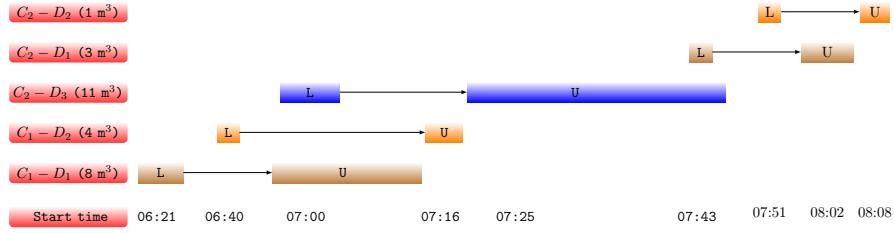


Figure 2: Schedule of the instance of Figure 1.

In this section, we represent the scheduling of a delivery node  $d$  as a pair of loading  $L_d$  and unloading  $U_d$  tasks. We then refer to a solution  $S$  as a set of loading and unloading tasks performed by a set of drivers during a particular day.

$$\begin{aligned}
L_d &= \{(b, k, q_d, v_b), b \in \mathcal{B}, k \in K\} \\
U_d &= (k, v_d, w_d), k \in K \\
S &= \left\{ \cup_{1 \leq j \leq n_o} (L_{d_o^j}, U_{d_o^j}), \forall o \in \mathcal{O} \right\}
\end{aligned}$$

#### 4.1 GRASP algorithm

The GRASP algorithm is an iterative suite of constructive and local search algorithms introduced by Feo and Resende [1995]. For each iteration, a feasible solution  $S$  is built using a greedy randomized algorithm. Then a local search algorithm investigates the neighborhood of  $S$  to find a local optimum. The pseudo-code of Algorithm 1 shows that the procedure returns the best overall solution (for a minimization problem) after some stopping conditions (time limit or a maximal number of iterations) are met.

---

##### Algorithm 1 Pseudo-code of the GRASP algorithm

---

**Input:**  $H$ : List of constructive randomized heuristics

---

```

1  $S^* \leftarrow \emptyset$     $Cost(S^*) \leftarrow \infty$ 
2 while Conditions not met do
3    $Cost(S') \leftarrow \infty$ 
4   for each  $h \in H$ 
5      $S \leftarrow h(S)$ 
6      $S \leftarrow LocalSearch(S)$ 
7     if  $Cost(S) < Cost(S')$  then
8        $S' \leftarrow S$ 
9       if  $Cost(S') < Cost(S^*)$  then
10         $S^* \leftarrow S'$ 
11 return  $S^*$ 

```

---

#### 4.2 Greedy randomized insertion algorithm

As referred to in Resende and Ribeiro [2019], the general outline of a greedy randomized algorithm used in the GRASP framework works as described in Algorithm 2. At each iteration, let's consider the set  $CL$  of candidate delivery nodes that are not yet scheduled. We note that, for our problem, not all delivery nodes are candidates for insertion at each

iteration, since deliveries of the same order are ordered, any order of a customer may be chosen, and it must be satisfied before switching to another order, and the number of visits to a customer is not known beforehand. We first initialize  $CL$  with the first delivery of a random order for each customer. We create the set  $CL'$  with elements of  $CL$  we deem promising for a better solution. We evaluate the increase in the cost function when incorporating each  $d \in CL'$  into the incumbent solution  $S$  and create a restricted candidate list  $RCL$  formed by nodes whose incremental costs are less than a defined threshold. From  $RCL$ , we randomly select the next delivery node to be incorporated into the incumbent solution and we determine its loading and unloading schedule with the procedure described in Algorithm 3. Next, we update  $S$  and the remaining quantities of the order and customer. Then we add to  $CL$  the next delivery node candidate. If an order  $o$  is not yet fulfilled after visiting  $d_o^j$ , the candidate is the next delivery node  $d_o^{j+1}$ . Otherwise, if the customer has remaining orders, the candidate is the first delivery node  $d_{o'}^0$  of another randomly selected order  $o'$ .

The greedy aspect of the GRASP is the creation of the  $RCL$  set, the probabilistic aspect is the random selection in  $RCL$ , and the adaptive aspect is the update of  $CL$  and the reevaluating of the incremental costs. We use the additional set  $CL'$  because we noticed that restricting  $CL$  to delivery nodes with the same demand, delivery due time, or overlapping unloading timeslots helps us intensify the search. Using  $CL'$  also helps improve the algorithm complexity by reducing the number of nodes to evaluate. To diversify the search we simply remove the filter component. We thus obtain four greedy randomized insertion heuristics for our GRASP framework.

---

**Algorithm 2** Greedy randomized insertion algorithm

---

**Input:**  $S$ : empty solution  $S$

---

```

1  $CL \leftarrow \emptyset$ 
2 for each customer  $i$ 
3   | Select a random order  $o_1 \in \mathcal{O}_i$ 
4   |  $CL \leftarrow CL \cup \{d_{o_1}^0\}$ 
5 while  $CL \neq \emptyset$  do
6   |  $CL' \leftarrow \text{Filter}(CL)$ 
7   | for each  $d \in CL'$ 
8     |  $C(d) \leftarrow$  incremental cost of inserting  $d$ 
9   |  $C_{min} \leftarrow \min \{C(d), d \in CL'\}, C_{max} \leftarrow \max \{C(d), d \in CL'\}$ 
10  |  $RCL \leftarrow \{d \in CL, C(d) \leq C_{min} + \alpha(C_{max} - C_{min})\}$ 
11  | Select random delivery node  $d_o^j$  of customer  $i$  from  $RCL$ 
12  |  $L_{d_o^j}, U_{d_o^j} = \text{ScheduleTasks}(d_o^j, S)$ 
13  |  $S \leftarrow S \cup (L_{d_o^j}, U_{d_o^j})$ 
14  |  $q_i \leftarrow q_i - q_{d_o^j}; q_o \leftarrow q_o - q_{d_o^j}$ 
15  | if  $q_o \neq 0$  then
16    |  $CL \leftarrow CL \cup \{d_o^{j+1}\}$ 
17  | else if  $q_i \neq 0$  then
18    | Select another order  $o' \in \mathcal{O}_i$ 
19    |  $CL \leftarrow CL \cup \{d_{o'}^0\}$ 
20  | Update  $CL$ 
21 return  $S$ 

```

---

Algorithm 3 takes as parameters a delivery node  $d_o^j$  of the customer  $i$  and a partial solution and looks for a plant and a driver available for loading and unloading operations.

383 For each driver  $k$  and plant  $b$  we simulate the loading and unloading operations while  
 384 checking the concrete lifespan constraints, and the plant and driver availability. For each  
 385 node, we first determine the start loading time  $SLT$  by subtracting  $t_{bi}$ ,  $\alpha_b$ , and the loading  
 386 duration  $LD_{d_o}^b$  to the expected delivery time  $EDT$ .  $EDT$  is either the arrival time  $a_i$  for  
 387 the first delivery of a customer or the end of the unloading of the precedent delivery. At line  
 388 15, we ensure with the procedure *FindDriverLoadingSlot* that the loading starts only if the  
 389 driver is present at the depot. The presence of the driver does not guarantee that the loading  
 390 dock is available, thus we use the procedure *FindDepotLoadingSlot* at line 16 to ensure that.  
 391 Once we know  $SLT$ , we can easily deduce the arrival time ( $AT$ ), start unloading time  
 392 ( $SUT$ ), driver waiting time ( $W_{d_o}^k$ ), and client waiting time ( $W_{d_o}^j$ ). We also keep track of the  
 393 driver's work duration. The algorithm returns the best loading and unloading operations  
 394 with the least cost. We keep track of all timeslots for a plant when its loading dock is  
 395 busy, and for a driver when he starts loading until the end of the unloading service. Within  
 396 *FindDepotLoadingSlot* (*FindDriverLoadingSlot*), we iterate through the timeslots of a depot  
 397 (driver) to schedule the current operation at a free timeslot. These allow us to insert the  
 398 scheduling of a node between existing schedules.

---

**Algorithm 3** Schedule loading and unloading tasks

---

**Input:** Partial solution  $S$ , delivery node  $d_o^j$

```

1 Function ScheduleTask( $d_o^j, S$ )
2    $n_i$ : last node visited for the customer  $i$ 
3    $\mathcal{LS}$  : Partial solutions list
4    $bestSol$   $Cost(bestSol) = +\infty$ 
5   for each driver  $k$ 
6      $n_k$ : current location of  $k$  (plant or delivery node)
7     for each plant  $b$ 
8       if  $t_{bi} \geq \delta$  then continue
9        $EDT = SUT = a_i$ 
10      if  $n_i \neq null$  then
11         $SUT = rand(EUt_{n_i} - \gamma/3, EUt_{n_i})$ 
12         $EDT = EUt_{n_i}$ 
13       $q_o^j = \min\{Q_k, q_o\} // q_o$  remaining demand of order  $o$ 
14       $SLT = EDT - t_{bi} - \alpha_b - LD_{d_o}^b$ 
15       $SLT = FindDriverLoadingSlot(b, n_k, SLT, LD_{d_o}^b)$ 
16       $SLT = FindDepotLoadingSlot(b, SLT, LD_{d_o}^b)$ 
17       $AT = SLT + LD_{d_o}^b + \alpha_b + t_{bi}$ 
18       $SUT = \max\{AT, EDT\}$ 
19       $W_{d_o}^k = \max\{0, SUT - AT\}$ 
20       $W_{d_o}^j = \max\{0, AT - EDT - \lambda_i\}$ 
21       $EUT = SUT + UD_{d_{ij}}^p$ 
22       $WT = WT_k + (EUT + \beta_k - SLT) + t_{n_k b} + t_{i,k}$ 
23       $TC = t_{n_k, b} + t_{b, i}$ 
24      if  $Cost(bestSol) < Cost(S) + TC$  then
25         $bestSol = (j, b, k, SLT) \cup (j, b, k, SUT)$ 
26         $Cost(bestSol) = Cost(S) + TC$ 
27  return  $bestSol$ 

```

---

399    **Local Search**

400    **5    Experimental results**

401    **5.1   Data sets**

402    **6    Conclusion**

403    **Acknowledgments**

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