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ORIGINAL PAPER

Optimizing the wine transportation process from bottling plants to ports

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Abstract

The wine industry is a highly competitive sector for which any efficiency improvement in the wine supply chain plays a critical role in maintaining or increasing profitability. Literature shows several successful applications of operational research tools at each stage of the wine production process. However, unlike other stages, the transportation and distribution phase has not been given the same attention in the specialized literature. To bridge this gap, this article proposes an integer linear programming model to jointly determine a plan for the bottling and transportation of products to ports in order to minimize inventory, freight, and delay costs. This model can be optimally solved in less than one day for small instances of up to 25 jobs. In practice, however, some industrial instances can easily exceed 200 jobs, which precludes the use of this model to support decision-making. To cope with this issue, we devise a two-stage procedure that generates good-quality solutions for industrial-size instances of this problem in reasonable computing times. Particularly, we show that the GAP of the proposed heuristic solution is relatively low for a wide range of instances. Finally, a case study is conducted on a medium-sized Chilean winery we worked with, where the planning generated by the proposed heuristic reduces the costs corresponding to the transportation stage by 45.3% in the best case, compared to the initial planning of the winery.

Keywords Wine supply chain · Transportation · Integer programming · Heuristic · Case study

1 Introduction

Winemaking in Chile dates back to the 16th century when Spanish conquerors began importing wine grapes into the country (Knowles and Sharples 2002). Following various attempts to improve its processes, Chile currently ranks as the world's

Extended author information available on the last page of the article seventh-largest wine-producing nation and the fourth-largest exporter. Furthermore, wine constitutes a significant contribution to the Chilean economy, representing 0.5% of GDP, and directly employing more than 100,000 people (WOC 2021).

In Chile, current per capita consumption stands at around 14 ls per annum, well below that of other countries with similar characteristics (OIV 2019). This particularity of the Chilean market began to take shape in the 1990s when the local wine industry entered the world stage. As a result, the Chilean wine sector became mainly export-driven, decreasing its interest in the national market and focusing on larger and far more competitive markets than the Chilean one (Varas et al. 2020b).

Furthermore, the expected profitability in the wine industry is not very high (Porter 2008). In fact, McMillan (2012) suggests that wine producers face a “hyper-competitive” business environment, which systematically diminishes their profits. Therefore, improving the efficiency of the supply chain becomes a critical factor to remaining competitive in a market that is increasingly global and competition increasingly intense (Garcia et al. 2012).

In general terms, the wine supply chain comprises four stages: the grape harvest, winemaking, bottling, and distribution (Basso et al. 2020). As we establish in the literature review, the first three have been studied in-depth using operations research tools. In contrast, in the context of the transportation and distribution phase of bottled wine, to the best of our knowledge, the only contribution in the specialized literature is Cholette (2007), which studies the problem of matching distributors and wineries. There are, alas, no studies that focus on the transportation of bottled wine using operations research tools, even though this process can generate high costs in the wine supply chain, which range from 11 to 24% of total costs (Marone et al. 2017).

In order to improve production efficiency within the wine industry, this article studies the process of transporting bottled export wine to ports. The problem lies in determining what day each job will be bottled and, once completed, deciding which truck will take it to the port. Planning aims for all the jobs of an order to be in port within a time window that ends immediately before the ship’s departure. In addition, the problem considers inventory costs at the bottling plant and the port and freight costs and fines in the eventuality of delays.

The contributions are threefold. First, we formulate an integer linear programming model that allows the scheduling of ground shipping from bottling plants to ports. Second, given the significant computation times of the exact solution using the CPLEX solver, we propose a constructive heuristic that makes it possible to solve large instances in less than one second. Third, we carry out a case study with data obtained from a medium-size winery located in Chile. Finally, we compare the winery’s developed plans with the heuristics’ solution, finding that the proposed approach considerably reduces the total costs associated with the transportation and distribution stage.

The rest of the article is structured as follows. Section 2 reviews the literature on the wine supply chain. In Sect. 3, the problem to be studied is described. Section 4 presents the integer linear programming model. Section 5 describes the proposed constructive heuristic, whereas Sect. 6 presents the case study of a Chilean winery. Finally, Sect. 7 presents the main conclusions of the study.

2 Literature review

Over recent decades, various industries worldwide have turned to operations research tools to improve logistics processes, increase revenues, and other sector-specific objectives. One such example is that of the agricultural and forestry management sectors, where operations research has been implemented since the 1950s (Ghosh et al. 2018). An area that has received a particular amount of attention is the agri-food supply chain, on which numerous studies have been carried out in multiple industries such as cheese (Ghadge et al. 2020), fresh meats (Riahi et al. 2018), and honey (Grivani and Pishvaee 2017). For further information on operations research applications in the agri-food sector, we refer the reader Taşkıner and Bilgen (2021).

In the agri-food industry, a relevant product is wine, perishable but with a long shelf life. In this regard, some articles have focused on modeling the entire chain. For example, Varsei and Polyakovskiy (2017) designs a sustainable supply chain structure in Australia based on a real case study. Fragoso and Figueira (2020) follows a similar approach, conducting a case study of the wine industry in southern Portugal. Also, Basso et al. (2023) proposes an horizontal collaboration approach for the entire wine supply chain. On the other hand, through data science tools, Ting et al. (2014) develops a decision support system for quality assurance in sustainable supply chains, with a case study on red wine. Finally, using sustainability science, some contributions (e.g., Christ 2014; Pattara et al. 2012; Neto et al. 2013) focus on the environmental impact of wine production.

Other studies have focused on particular processes within the wine supply chain, using operations research tools (Moccia 2013). According to Basso et al. (2020), the wine supply chain comprises four stages: the grape harvest, winemaking, packaging, and distribution.

The grape harvest stage is comprised mainly of agricultural tasks. One pioneering contribution is Ferrer et al. (2008), which uses a mixed-integer linear programming model (MILP) for tackling the grape harvest planning problem, taking both the operational costs and the quality of the grape into account. Later, Arnaout and Maatouk (2010) develops a new heuristic to solve large instances for the problem presented by Ferrer et al. (2008). For this same problem, Bohle et al. (2010) presents a robust optimization approach to consider uncertainty in manual and automatic harvest productivity, while Varas et al. (2020a) considers a multi-objective approach to reconcile the trade-off between maximizing grape quality and minimizing logistics costs. On this, Varas et al. (2022) propose a collaborative grape harvesting approach in which multiple wineries are able to share workers and harvesting machinery. Furthermore, the authors devise an entropy-based sharing method to split the collaborators' costs.

The second stage corresponds to winemaking, which includes all the activities necessary, from processing the grape to aging the wine. Cakici et al. (2006) presents a MILP model to generate routes for the pipe network in a tank at a winery located in California. The authors aim to minimize wine damage and optimize network resources. Given the scale of the resulting problem, the authors propose a heuristic-based solution approach capable of finding a solution in seconds. Palmowski and Sidorowicz (2020) applies a dynamic programming approach in order to find an optimal strategy for assigning grapes to pressing tanks. Additionally, Carneiro et al. (2021) proposes a metaheuristic to optimize the scheduling of machines in a grape reception plant to improve the quality of the wine while also keeping logistics costs low.

The third stage corresponds to the bottling and packaging process. At this stage, Cholette (2009) presents a two-stage stochastic linear program with a fixed resource that maximizes the expected benefit over a given distribution of demand scenarios, mitigating the production misallocation from warehouses to sales channels. More recently, Basso and Varas (2017) proposes a MILP model and a heuristic algorithm to obtain a bottling schedule, considering operational constraints such as setup times and wine oxidation. For the same problem, Basso et al. (2020) proposes a collaborative approach between wineries. The authors propose a maximum entropy methodology that simultaneously solves the problems of coalition formation and cost-sharing. Varas et al. (2018) extends the work presented in Cholette (2009) by analyzing the impact that delaying the labeling of bottled wines has on productive efficiency. The authors develop a multistage mixed-integer stochastic programming model and find that some postponement level is always desirable. Varas et al. (2019) proposes a $(s-1, s)$ policy for managing premium wines inventory. In particular, the authors approximate the dynamics of the labeling process by a group scheduling policy to obtain the mean delays for each labeled product and solve a newsvendor-type problem for each end-product.

Finally, the transportation and distribution stage includes all of the activities necessary for the product to reach the end consumer. To the best of our knowledge, the only article that uses operations research at this stage is Cholette (2007), which proposes a distribution model for suggesting profitable pairings between distributors and wineries.

From the literature review, we conclude that there is a research gap regarding the use of operations research tools in the transportation stage of the wine supply chain. The adoption of OR methodologies lag behind at this stage, in stark contrast to other agri-food sectors such as milk (Sethanan and Pitakaso 2016), wood (Rummukainen et al. 2009), fishing (Zhang et al. 2019), and fruit (Quintero Ramirez et al. 2019), among others.

While we focus on optimizing the wine transportation process from bottling plants to ports, the contributions of our research are relevant in a broader scope. Indeed, the assignment of jobs to a bottling day subject to machines' capacity constraints can be viewed as a *generalized assignment problem*, which has been widely studied in the literature (LeBlanc et al. 1999). Moreover, the assignment of packed jobs to trucks, the second relevant decision variable, can be reduced to a *bin packing problem* which has been extensively studied in the past (Martello and Toth 1990).

Since the wine transportation problem can be reduced to a bin-packing problem, which is known to be NP-hard (Simchi-Levi 1994), we devise a two-stage procedure to generate good-quality solutions for industrial-size instances of this problem. Focusing on feasibility, we develop a new constructive heuristic that focuses on minimizing inventory costs. A similar approach is followed in Basso and Varas

(2017) and Basso et al. (2019). To improve the quality of the incumbent solution, we implement a Fix-and-Optimize procedure. First introduced as *Exchange Heuristic* by Pochet and Wolsey (2006), Fix-and-Optimize is a common MIP-based heuristic where, at each iteration, all variables except small group are fixed to the value of the incumbent solution and the free variables are optimized (Joncour et al. 2023). Some relevant applications of the Fix-and-Optimize approach include multi-level capacitated lot sizing problems (Helber and Sahling 2010), production and distribution planning (Sel and Bilgen 2014) high school (Dorneles et al. 2014) and university (Lindahl et al. 2018) timetabling problems.

3 Description of the problem

This work is conducted in the context of a cooperation with a medium-size Chilean winery located near the town of San Clemente in the Maule Region. The winery produces high-quality wines focusing on export, with international markets representing 80% of the winery's total sales. This work aims to support its decision-making in the transportation process when exporting products. In this regard, the winery manages its exports Free On Board (FOB). In this way, the framework for action of the distribution process ends once the merchandise is delivered at the port of shipment, with the buyer responsible for maritime shipping ground shipping in the destination country, among others.

Figure 1 shows each of the processes that take place in the transportation stage, which starts with the arrival of orders (Step 0). Each order must be available at the port within a defined time window. Usually, each order is associated with a single buyer's request and comprises one or more jobs. Each job considers a single type of wine and may vary in volume, bottle, and cork type.

Once an order is placed, the jobs within it are assigned individually to bottling lines depending on their capacity availability. In this step (Step 1), the bulk wine stored in the tanks is bottled. Although this research focuses primarily on the transportation process, in order to study this stage more effectively, we consider a tactical approach for bottling planning, which determines the day of bottling for each job. For a more operational view of the wine bottling process, including intraday decisions (e.g., jobs ordering), we refer the reader to Basso and Varas (2017).

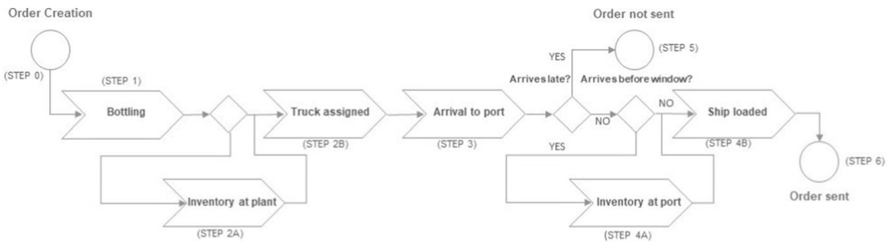

Fig. 1 Flow diagram of the orders in the wine distribution process

Our article assumes that each job in an order can be bottled on different dates. Therefore, each order will be considered ready once all the jobs are bottled. When a job is bottled, it can be held in a storage facility at the winery (Step 2a) or immediately assigned to a truck bound for the port (Step 2b). When held at the bottling plant, the firm incurs inventory costs which depend on the volume and total days each job is stored.

The winery we worked with has a contract agreement with a logistics provider responsible for carrying the jobs to the port through a fleet of trucks large enough to suit the winery's needs. Each requested truck has a daily fixed cost. We assume that the job is available in port the day after shipment.

When one or more jobs are assigned to a truck, and it arrives at the port (Step 3), there is the option of directly loading the jobs onto the container ship (Step 4b) or, alternatively, placing them in a warehouse next to the port (Step 4a). The first option is used when the jobs arrive at the port within the defined time window. As for the second option, when one or more jobs of the order arrive before the start of the time window, they must be stored in a port warehouse, incurring costs depending on the volume and the total number of days. In practice, the cost associated with inventory in port is considerably higher than the inventory costs at the bottling plant.

Once the time window starts, jobs found at the port warehouse are immediately loaded on the carrier vessel. If one or more jobs of an order do not arrive at the port before the time window ends, the entire order is not shipped. This last entails a compensation payment by the winery to the buyer for non-fulfillment of the order (Step 5).

When the order is completed at the port, the winery must provide Customs with all necessary documentation. Once all handling has been carried out and the shipping process is finished, the winery must notify the buyer that the order is in transit (Step 6).

In summary, the problem we study in this paper consists of supporting decision makers to handle two relevant logistics decisions: which day to bottle each job and, once bottled, to determine which day the job should be transported to the port. These decisions are constrained by bottling and truck capacities. The objective is to minimize the winery's transportation costs, including truck rental costs, inventory costs, and compensation payments for delays.

4 An integer linear programming model

This section presents an integer linear programming (IP) formulation for the wine transportation problem described in the previous section. In particular, Sects. 4.1 and 4.2 establish the sets and parameters of the model, respectively. In Sect. 4.3, the decision variables are defined, while in Sect. 4.4 the constraints are described. In Subsection 4.5, the objective function of the model is established. An illustrative example is presented in Sect. 4.6. Finally, Sect. 4.7 determines the maximum number of jobs for which CPLEX can be used as a resolution method.

4.1 Sets

The sets used in the model are as follows:

N	: Jobs (indexed by n).
O	: Orders (indexed by o).
K	: Trucks (indexed by k).
$I_o \subseteq N$	: Jobs belonging to the order o.
$\{1, \dots, T\}$	: Periods (indexed by t).

4.2 Parameters

The parameters used in the model are as follows (the acronym CLP means Chilean Pesos):

T	: Planning horizon.
L_o	: Lower bound of the time window of order o.
U_o	: Upper bound of the time window of order o.
CT	: Fixed cost of using a truck during one period [CLP].
$CAPC_k$	: Capacity of truck k[$Liters$].
$CAPE$	: Bottling capacity [$Liters \cdot Period$].
VOL_n	: Volume of job n[$Liters$].
α	: Inventory cost at port [$\frac{CLP}{Liters \cdot Period}$].
β	: Inventory cost at bottling plant [$\frac{CLP}{Liters \cdot Period}$].
λ	: Compensation payment for missing vessel [CLP].
M	: Large enough constant.

4.3 Variables

The variables used in the model are as follows:

x_{kt}	: 1 if truck k is used during period t, 0 otherwise.
y_{nt}	: 1 if job n is bottled during period t, 0 otherwise.
z_{nkt}	: 1 if job n is sent on truck k during period t, 0 otherwise.
l_o	: 1 if order o does not arrive within the time window, 0 otherwise.
$s_n \in \mathbb{N}$	: Period on which job n is ready to be boarded after being transported.
$v_n \in \mathbb{N}$	: Period on which job n is ready to be transported after bottling.
$f_o \in \mathbb{N}$	: Period on which all jobs of the order o are in port.
$ep_n \in \mathbb{N}$	: Positive part of $L_o - s_n$.

4.4 Constraints

The constraints of the model are as follows:

$$\sum_{k\in K}\sum_{t=1}^{T} z_{nkt} \leq 1 \quad \forall n \tag{1}$$

$$f_o \geq s_n \quad \forall o, n \in I_o \tag{2}$$

$$z_{nkt} \leq 1 - \sum_{\hat{t}=t}^{T} y_{n\hat{t}} \quad \forall n, k, t \tag{3}$$

$$z_{nkt} \leq \sum_{\hat{t}=1}^{t-1} y_{n\hat{t}} \quad \forall n, k, t \tag{4}$$

$$\sum_{n\in N} VOL_n \cdot y_{nt} \leq CAPE \quad \forall t \tag{5}$$

$$\sum_{n\in N} VOL_n \cdot z_{nkt} \leq CAPC_k \quad \forall t, k \tag{6}$$

$$v_n = \sum_{t=1}^{T} y_{nt} \cdot t + 1 + \left(1 - \sum_{t=1}^{T} y_{nt}\right) \cdot (T-1) \quad \forall n \tag{7}$$

$$s_n = \sum_{k\in K}\sum_{t=1}^{T} z_{nkt} \cdot t + 1 + \left(1 - \sum_{k\in K}\sum_{t=1}^{T} z_{nkt}\right) \cdot T \quad \forall n \tag{8}$$

$$L_o - s_n \leq ep_n \quad \forall o, n \in I_o \tag{9}$$

$$f_o - U_o \leq M \cdot l_o \quad \forall o \tag{10}$$

$$s_n \geq v_n + 1 \quad \forall n \tag{11}$$

$$z_{nkt} \leq x_{kt} \quad \forall n, k, t \tag{12}$$

$$x_{kt}, z_{nkt}, y_{nt}, l_o \in \{0, 1\} \quad \forall n, o, k, t \tag{13}$$

$$s_n, v_n, f_o \in \mathbb{N} \quad \forall n, o \tag{14}$$

$$ep_n \in \mathbb{N} \bigcup \{0\} \quad \forall n \tag{15}$$

Constraint (1) states that each job must be assigned to a single truck and a single day. Constraint (2), together with the objective function, defines variable f_o as the period in which all the jobs of the order are at the port. Constraints (3) and (4) ensure that a job can be assigned to a truck if and only if it was bottled previously. Constraints (5) and (6) establish the maximum bottling capacity per period and per truck, respectively. For each job, Constraint (7) defines the ending time of the bottling process, while Constraint (8) defines the arrival time at the port. Constraint (9), together with the objective function, defines the variable ep_n as the job arrival earliness prior to the lower bound of the corresponding time window. Constraint (10) ensures that l_o takes value 1 if the order arrives late to port. Constraint (11) indicates that a job must arrive at the port at least one day after being bottled. Constraint (12) ensures that x_{kt} takes value 1 when truck k is used during period t. Constraints (13), (14) and (15) correspond to the nature of the variables.

4.5 Objective function

The objective function (16) of the model seeks to minimize the total costs of the winery's transportation process by way of five terms. The first term represents the total cost of truck rental. The second and third term corresponds to the port and bottling plant inventory costs. The fourth term corresponds to the compensation payment entailed by not sending the order on time. Finally, the fifth term, together with Constraint (2), allows us to define the variable f_o as the period in which all the jobs of the order o are available at the port.

$$\min \sum_{k \in K} \sum_{t=1}^{T} CT \cdot x_{kt} + \sum_{n \in N} \alpha VOL_n \cdot ep_n + \sum_{n \in N} \beta VOL_n \cdot (s_n - v_n - 1) + \sum_{o \in O} \lambda \cdot l_o + \sum_{o \in O} \frac{1}{M} \cdot f_o \tag{16}$$

4.6 Illustrative example

This section presents an illustrative instance generated using synthetic data to illustrate better the application of the proposed IP model. This data can be found in Tables 7 and 9 in the Appendix. This instance consists of four orders, each with different time windows. There are three jobs within each order, each of different volumes, thus obtaining a total of twelve jobs. The model is encoded in AMPL and solved with CPLEX on a notebook with an Intel (R) Core (TM) i5-10300 H CPU @ 2.50GHz and 8 GB of RAM.

Figure 2 illustrates the optimal solution. The orders and their respective jobs are displayed on the left-hand side. The planning horizon and the time windows for each of the four orders appear at the top. The optimal planning is shown at the center of

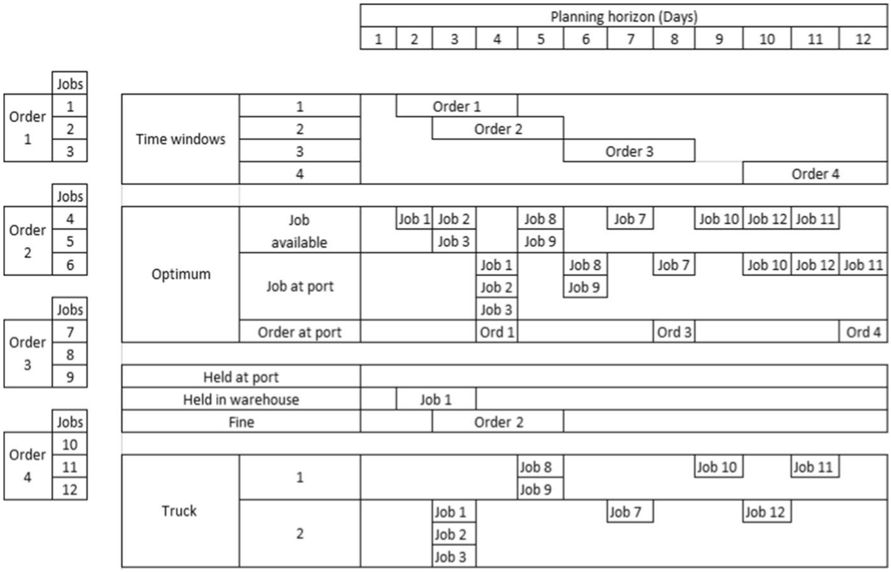

Fig. 2 Illustrative example

the figure. This planning involves the bottling and port arrival dates and the storage periods. Finally, at the bottom, we report the daily use of the trucks.

4.7 The curse of dimensionality

In this subsection, we generate synthetic instances for an increasing number of jobs in order to determine to what extent the model can provide an optimal solution in

Table 1 Computational results of the IP model in 15 test instances

Orders	Total jobs	Periods	IP OF	IP Time (s)
2	10	16	1,800,000	0.97
2	10	24	1,800,000	28.22
2	10	33	1,800,000	13.68
3	15	48	3,000,000	150.72
3	15	72	3,000,000	140.62
3	15	97	3,000,000	180.74
4	20	50	3,647,137	380.47
4	20	75	3,647,137	570.17
4	20	101	3,647,137	570.68
5	25	41	3,600,000	65864.6
5	25	78	3,600,000	66328.6
5	25	105	3,600,000	66014.0
6	30	50	–	> 86400
6	30	75	–	> 86400
6	30	101	–	> 86400

less than one day. Table 1 shows the results, indicating the number of orders and jobs considered in each instance, the optimal value (IP OF), and the computation time (IP Time). As expected, computation time grows exponentially with the number of jobs and cannot find an optimal solution for 30 jobs in less than a day.

In practice, real-sized instances can easily exceed 100 jobs, which precludes the use of CPLEX in a production environment. We present a heuristic resolution approach in the following section to tackle this issue.

5 A two-stage heuristic procedure

As shown in Table 1, for more than 30 jobs, it is impossible to solve the wine bottling and distribution problem in less than one day, which precludes the use of the IP model for supporting decision-making in practice. To tackle this issue, in this section, we propose a two-stage heuristic procedure that constructs a feasible solution in a reduced computing time and then iteratively improves the solution.

For the sake of the exposition, this section is structured as follows. Section 5.1 describes the greedy heuristic algorithm, whereas Sect. 5.2 reports several computational times when solving large instances. Then, Sect. 5.3 comprehensively describes the matheuristic. Finally, Sect. 5.4 analyzes the heuristic performance by focusing on the gap.

5.1 The greedy heuristic

This subsection presents a constructive heuristic that focuses on minimizing inventory costs. Particularly, the heuristic tries to bottle the jobs near to the end of the corresponding order time window. Then, bottled jobs are assigned to trucks as soon as possible. The heuristic considers the following variables:

$$y_{nt} \in \{0,1\} : \text{It takes value 1 if the job } n \text{ is bottled during the period } t, \text{ and 0 otherwise.}$$

$$z_{nkt} \in \{0,1\} : \text{It takes value 1 if the job } n \text{ is sent on the truck } k \text{ during the period } t, \text{ 0 otherwise.}$$

$$s_n \in \{1,\dots,T\} : \text{Period on which the job } n \text{ arrives at the port.}$$

$$v_n \in \{1,\dots,T\} : \text{Period on which the job } n \text{ is bottled.}$$

$$CAPE_t \geq 0 : \text{Bottling residual capacity in period } t.$$

$$CAPC_{kt} \geq 0 : \text{Truck k residual capacity in period } t.$$

Algorithm 1 presents a pseudocode of the heuristic. Lines 1 and 2 initialize the residual bottling and transportation capacities, respectively. Line 3 sorts the orders decreasingly by total volume, so larger orders are assigned first. In line 5, jobs within the same order are also sorted decreasingly by volume. Lines 4 to 15 ensure that each job n is bottled both during a period with enough residual capacity and closer to the time window upper bound U_o. In cases with insufficient residual bottling capacity on period t, the algorithm tries to bottle the job on the previous period $t-1$. Lines 16 to 28 ensure that each job n is shipped as soon as possible after bottling. Line 18 ensures that the fleet size is minimal at each period. If there is insufficient residual transport capacity in period t, an attempt to ship is made on period $t+1$.

Algorithm 1 Constructive heuristic pseudocode

```
Input: Problem data: O,N,VOL,L,U,K,T,CAPE
1:  CAPE_t ← CAPE
2:  CAPC_{kt} ← CAPC_k
3:  sort O in decreasing order by total volume \sum_{n∈I_o} VOL_n
4:  for o ∈ O do
5:      sort I_o in decreasing order by volume VOL_n
6:      for n ∈ I_o do
7:          for t ∈ U_o − 2, ..., 1 do
8:              if VOL_n ≤ CAPE_t then
9:                  y_{nt} ← 1
10:                 v_n ← t                         ▷ The job is assigned to period t.
11:                 CAPE_t ← CAPE_t − VOL_n         ▷ update the residual bottling capacity
12:             end if
13:         end for
14:     end for
15: end for
16: for t ∈ {1, ..., T − 1}, n ∈ N : y_{nt} = 1 do
17:     for \hat{t} ∈ {t + 1, ..., T} do
18:         sort K in increasing order by the residual capacity CAPC_{k\hat{t}}
19:         for k ∈ K do
20:             if VOL_n ≤ CAPC_{k\hat{t}} then
21:                 z_{nk\hat{t}} ← 1
22:                 s_n ← \hat{t} + 1               ▷ The job arrives at port during period \hat{t}+1.
23:                 CAPC_{k\hat{t}} ← CAPC_{k\hat{t}} − VOL_n   ▷ update residual truck capacity
24:                 Go back to step 16
25:             end if
26:         end for
27:     end for
28: end for
```

Table 2 Computing times for large-size instances

Jobs	OS OF	IP time (s)	GH OF	GH Time (s)
200	–	>86,400	19,840,000	<1
300	–	>86,400	29,536,900	<1
400	–	>86,400	38,920,400	<1
500	–	>86,400	47,377,200	<1

5.2 The effectiveness of the greedy heuristic when tackling large-size instances

This subsection shows the effectiveness of the proposed constructive heuristic when solving large-size instances. To do so, we generate several synthetic instances ranging from 200 to 500 jobs to be bottled and moved. Table 2 shows the objective function value of the solution found by the greedy heuristic (GH OF) and the corresponding computing time (GH Time). The results show that the proposed heuristic takes less than one second to find a solution for all the instances analyzed, whereas CPLEX cannot find a feasible solution within a day of computing time.

5.3 The improvement matheuristic

To improve the solution generated by the greedy heuristic procedure, we develop a matheuristic approach that builds on a fix-and-optimize framework. On this, first, note that new solutions can be generated by reallocating jobs in the bottling and shipping schedule. Based on the notation stated in Sect. 4, this implies modifying the values of variables y_{nt} and z_{nkt}. The devised approach focuses on modifying these variables for a given subset of jobs, while keeping all the rest of variables fixed, which allows to reduce the computational burden. In particular, our algorithm optimally reallocates all the jobs within the same order assuming that the remaining jobs remain fixed. Let $o \in O$ be a particular order. Then, the optimal reallocation of the jobs in the order o requires solving a new IP, which is identical to the integer programming problem discussed in Sect. 4, but for which the binary variables y_{nt} and z_{nkt} for all jobs $n \notin I_o$ are fixed to the values of the incumbent solution.

A pseudo-code for the matheuristic procedure is provided in Algorithm 2. It starts with an initial solution, which, in this case, is the feasible solution provided by the constructive algorithm. Then, at each iteration, the algorithm creates card (O) neighbor solutions by solving the reduced IP associated with each order $o \in O$. If no neighbor has a better cost than the incumbent, the algorithm stops and returns the current feasible solution. Otherwise, the incumbent is updated to the neighbor with minimum cost.

Algorithm 2 Improvement heuristic pseudo-code

Input: Initial feasible solution $\tilde{S}$ with cost $\tilde{C}$, problem data: O,N,VOL,L,U,K,T,$CAPE$,$CAPC_k$

```
while true do
    for o ∈ O do
        solve the IP sub-problem for order o using a state-of-the-art solver such as CPLEX
        define S^o the solution of the subproblem and C^o the cost.
    end for
    set ô ← arg min_{o∈O} C^o
    if C^ô < C̃ then
        update the incumbent S̃ ← S^ô
        update the incumbent cost C̃ ← C^ô
    else
        return the incumbent solution S̃
    end if
end while
```

The proposed improvement heuristic requires solving $|O|$ IPs at each iteration, yet these problems are smaller than the original problem as the number of jobs is reduced.

5.4 The performance of the two-stage heuristic algorithm

This subsection addresses the quality of the heuristic solutions in terms of the optimality gap.

First, Table 3 shows the gap between the output of the constructive heuristic and the reported optimal CPLEX solution for different numbers of jobs and orders. On this, the maximum gap value corresponds to the instance with 20 jobs, with a gap of 26.1%.

Table 3 Average performance of the heuristics

Jobs	IP		Greedy		Limited Time		Fixed Periods		One shot	
	GAP (%)	Time (s)	GAP (%)	Time (s)	GAP (%)	Time (s)	GAP (%)	Time (s)	GAP (%)	Time (s)
10	0.0	3.4	9.8	$\ll 1$	0.0	0.8	4.9	0.1	3.0	5.0
15	0.0	1709.4	17.8	$\ll 1$	0.0	60.8	15.3	0.2	11.7	12.1
20	0.0	2439.3	26.1	$\ll 1$	4.5	112.1	23.8	1.0	18.1	19.3
25	1.8	25,310.7	20.1	$\ll 1$	1.0	199.7	13.3	2.6	11.2	6.5

On the other hand, since the improvement heuristic requires to solve several integer programming problems, its implementation in real-sized instances does not reach the stop criterion within hours. To overcome this issue, we propose three settings that reduce the computational time.

- **Limited Time (LT).** Here each subproblem is solved by CPLEX with a time limit of 60 s. Whenever the time limit is reached, CPLEX returns the best solution founded so far. Note that the subproblems always start from a feasible solution.
- **Fixed Periods (FP).** In this setting, we assume that the reallocation of the jobs in order $o \in O$ is done within the same time interval as in the original solution. For this, for the the initial feasible solution, we define the interval $T(o) := [\underline{t}_o, \bar{t}_o]$, where $\underline{t}_o$ is the period in which order o starts to be bottled, and $\bar{t}_o$ is the period in which the order o is completed at port. For instance, in the illustrative example of Fig. 2, the time interval of order 3 is $T(3) = [4, 8]$ because the first jobs are bottled on day 4, and the order is ready at the port on day 8. Then, the reduced IP is solved only for the variables y_{nt} and z_{nkt} for $n \in I_o$ and $t \in T(o)$, with the rest of the variables fixed. No time limit is imposed.
- **One Shot (OS).** Finally, we consider that Algorithm 2 only performs one iteration of the main loop, with no time limit nor constraints over the time periods.

Table 3 shows the average GAP and time for 10 experiments using $n \in \{10, 15, 20, 25\}$. For each of these 50 instances, we solve the problem and compute the GAP using all the methods presented above. Figure 3 shows a box plot based on the calculated gaps. The standard deviations do not show a clear pattern for the greedy heuristic, with the deviation associated with 25 jobs being the one with

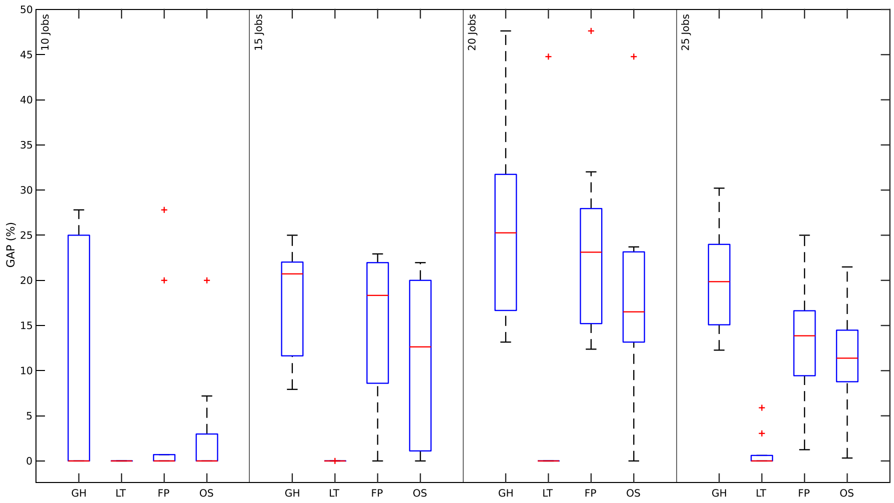

Fig. 3 GAP for the greedy heuristic and the matheuristics proposed

the lowest value. On the other hand, the matheuristics with Fixed Periods and One Shot behave similarly in average and standard deviation, improving over the greedy heuristic. The matheuristic with Limited Time exhibits the best performance with zero GAP for 10 and 15 jobs.

6 Case study

In this section, we conduct a case study to illustrate better the benefits of using the model and heuristics. The case focuses on a medium-size export-focused unnamed winery located in San Clemente, in the Maule Region (Fig. 4). Most of the winery's products are exported through the port of San Antonio in the Valparaíso region to China and Brazil.

Fig. 4 Location of the winery

Table 4 Orders received in April 2021

Order	No. of jobs	Volume (lts)	Completion date (f_o)	Arrival date at port	Lower limit (L_o)	Upper limit (U_o)
177/21	1	10,800	6	33	32	34
178/21	1	10,800	7	32	31	33
179/21	1	10,800	8	33	32	34
180/21	2	10,800	4	33	32	34
181/21	1	10,800	5	33	32	34
182/21	1	10,800	11	33	32	34
183/21	1	10,800	8	33	32	34
184/21	1	10,800	11	32	31	33
185/21	2	10,800	7	33	32	34
188/21	9	13,257	39	49	48	50
189/21	14	15,660	32	58	57	59
190/21	16	14,043	25	43	42	44
191/21	15	15,450	40	58	57	59
192/21	20	14,499	34	49	48	50
193/21	8	27,540	35	40	39	41
194/21	5	24,300	42	42	41	43
195/21	6	15,300	21	21	20	22
196/21	8	35,755	32	34	33	35
197/21	2	19,800	21	34	33	35
199/21	2	885	21	49	48	50
201/21	2	3150	27	35	34	36
202/21	4	18,000	35	35	34	36
203/21	6	15,066	35	35	34	36
207/21	5	5778	33	39	38	40

Table 4 shows the information for all the orders of April 2021. In particular, the first column corresponds to the order's identifier used by the winery. The second and third columns correspond to the number of jobs and the total volume for each order. The fourth and fifth columns indicate the time window of each order. Finally, the sixth and seventh columns indicate the current planning of the winery, that is, the day on which all the jobs of each order are bottled, and the day the order arrives at the port, respectively.

The winery provides us also with information about each job contained in the orders. Table 5, for example, shows the details for order 188/21, which includes the volume of each job, the date on which it is bottled, and the planned arrival of each job to the port. A complete description of the orders is provided in "Appendix A".

Table 5 Example information of Order 188/21

Order	Jobs	Volume of job (VOL_n)(lts)	Bottling date (v_n)	Arrival date at port (s_n)
188/21	1	540	6	49
	2	648	6	49
	3	648	8	49
	4	648	11	49
	5	648	11	49
	6	2700	11	49
	7	2025	13	49
	8	3375	14	49
	9	2925	22	49

The winery bottling and transportation approaches are as follows. The winery schedules the bottling process prioritizing first by volume, where higher volume jobs have priority over those of a lower volume since higher-volume jobs take longer to bottle. In the case of similar volumes, priority is given through the FIFO policy (First In, First Out) considering the date of entry. Then, the bottled jobs are held in the bottling plant until the order is entirely completed since all jobs of the same order are sent to port simultaneously. Finally, the shipment occurs when the order is wholly bottled and the time window begins. To simplify planning, the winery does not currently allow two different orders to be transported on the same truck, regardless of the residual capacity of the truck.

To evaluate the heuristic performance, we compare the proposed approach with the schedule generated by the winery. For this, the data presented in Tables 4 and 8 of Appendix A are considered using the parameters of Table 10. The planning results, as well as their associated costs (in Chilean pesos), are shown in Table 6.

Table 6 shows that the cost of the greedy heuristic is 37.1% lower than that of the planning used by the winery in reality. This reduction can be explained, among other factors, because the winery bottles the jobs in advance, which must be stored for extended periods, incurring high inventory costs. On the other hand, the heuristic assigns jobs to be bottled as close to the order time window as possible, minimizing the plant inventory cost. Furthermore, the winery planning always considers the

Table 6 Cost comparison between the winery's planning and the proposed heuristics (in Chilean Pesos)

	Trucks cost	Inventory cost at winery	Inventory cost at port	Compensation payments	Total costs
Winery planning	21,000,000	16,830,326	0	0	37,830,326
Greedy heuristic	21,600,000	0	2,215,200	0	23,815,200
Time limited	18,600,000	50,400	2,040,990	0	**20,691,390**
Fixed periods	19,800,000	58,118	2,419,260	0	22,277,378
One shot	21,600,000	0	2,040,990	0	23,640,990

complete shipment of the order, while the proposed approach makes it possible to send partial orders. That is to say, in several trucks and different periods. The latter increases the number of trucks to be used but offers greater flexibility in planning. Since the heuristic seeks to send the bottled jobs to the port as soon as possible, the inventory costs in port increase compared to the winery's planning. However, this increase is compensated by the reduction in inventory costs at the winery plant.

Concerning the use of the matheuristic, the resulting solutions attain a cost reduction ranging from 37.5 to 45.3% compared to the approach used by the winery. Furthermore, compared to the solution of the greedy heuristic, the improved solutions use fewer trucks while maintaining a similar inventory at the port. This is explained by the matheuristics strategy, which looks for optimal reallocation of the jobs in every order. Consequently, we obtain a more efficient planning that uses inventory at the winery to store jobs for a short period and then ship them simultaneously with other jobs, reducing less-than-full trucks and fleet size.

7 Conclusions

For years, operations research has been one of the most used tools by industries worldwide, helping them reduce costs, increase revenues, and minimize waste, among other benefits. In particular, multiple efforts have been made in the wine industry at different supply chain stages. However, the transportation stage is lagging behind. To the best of our knowledge, there are no contributions that use operations research tools or methodologies at this stage.

This paper addresses the final part of the wine supply chain, analyzing the bottling phase with the transportation process from the plants to the port simultaneously. This research, which aims to determine a transportation schedule that minimizes the costs of wine bottling and transportation to the port, contributes to the literature by developing an integer programming model to support decision-making in this context. Regarding the solution process, first, we solve the problem using state-of-art solvers such as CPLEX. We show that this approach is helpful for small instances only. For medium-sized instances, this approach becomes impractical as the solution times exceed those required by decision-makers. To tackle this issue, we propose a constructive heuristic that finds feasible solutions for real-size instances in less than a second. Furthermore, to improve the solution generated by the constructive heuristic, we develop a matheuristic approach that builds on a fix-and-optimize framework. To assess the perfomance of the proposed approaches, we compare the cost of the solutions generated with the optimal solution for instances up to 25 jobs. We find that our best approach is able to find solutions in minutes with an average GAP below 5%. Furthermore, the largest GAP is below 10% for all the instances.

Moreover, we conduct a case study using real information from a Chilean winery. The results show that the use of our heuristic approach reduces total costs by 45.3%.

This reduction can be explained because the current winery planning strategy bottles very early and, in turn, for simplicity, only sends fully completed orders. Consequently, high inventory costs are incurred at the bottling plant. On the contrary, the proposed heuristic generates schedules such that the job bottling is done close to the time window upper bound. Additionally, our model offers greater flexibility by sending partial orders, which translates to a reduction in inventory cost at the winery plant.

Finally, several directions for further research remain of interest. First, a future research line involves improving the quality of the proposed solutions by integrating the constructive heuristic with an improvement metaheuristic. Also, it would be interesting to study the impact of incorporating uncertainty into the model, for example, in the port time window. At present, these parameters are subject to substantial variations due to the presence of swells in the ports of Valparaíso and San Antonio, which may worsen due to climate change. A multi-stage stochastic programming approach or an affinely adjustable robust optimization approach could tackle this issues properly.

Jobs and orders data

See Tables 7, 8.

Table 7 Orders data of the illustrative example

Order	Lower limit (l_o)	Upper limit (u_o)	Jobs	Volume of jobs (VOL_n) (lts)
1	2	4	1	30
			2	70
			3	90
2	3	5	4	120
			5	110
			6	80
3	6	8	7	80
			8	60
			9	100
4	10	12	10	110
			11	120
			12	150

Table 8 Jobs data of the case study

Order	Jobs	Volume of job (VOL_n)(lts)	Bottling date (v_n)	Arrival date at port (s_n)
177/21	1	10,800	5	33
178/21	2	10,800	6	32
179/21	3	10,800	6	33
180/21	4	2556	1	33
	5	8244	1	33
181/21	6	10,800	4	33
182/21	7	10,800	8	33
183/21	8	10,800	7	33
184/21	9	10,800	7	32
185/21	10	5400	4	33
	11	5400	6	33
188/21	12	540	6	49
	13	648	6	49
	14	648	8	49
	15	648	11	49
	16	648	11	49
	17	2700	11	49
	18	2025	13	49
	19	3375	14	49
	20	2025	22	49
189/21	21	300	12	58
	22	135	13	58
	23	225	13	58
	24	225	13	58
	25	8700	15	58
	26	1104	15	58
	27	675	15	58
	28	225	15	58
	29	600	20	58
	30	96	25	58
	31	2700	25	58
	32	225	28	58
	33	450	32	58
190/21	35	270	11	43
	36	552	12	43
	37	552	12	43
	38	552	12	43
	39	270	12	43
	40	252	13	43
	41	252	13	43
	42	3420	14	43
	43	810	14	43
	44	2430	15	43
	45	540	15	43

Table 8 (continued)

Order	Jobs	Volume of job (VOL_n)(lts)	Bottling date (v_n)	Arrival date at port (s_n)
	46	540	19	43
	47	1800	19	43
	48	540	20	43
	49	1104	20	43
	50	1104	25	43
191/21	51	900	12	58
	52	300	12	58
	53	225	13	58
	54	225	13	58
	55	225	13	58
	56	450	14	58
	57	1800	14	58
	58	600	15	58
	59	225	15	58
	60	1200	20	58
	61	5400	25	58
	62	3000	25	58
	63	225	32	58
	64	675	33	58
192/21	66	270	11	49
	67	1272	12	49
	68	552	12	49
	69	540	12	49
	70	252	13	49
	71	252	13	49
	72	540	14	49
	73	1350	14	49
	74	810	15	49
	75	1620	15	49
	76	900	19	49
	77	270	20	49
	78	720	20	49
	79	552	20	49
	80	1104	25	49
	81	252	25	49
	82	540	28	49
	83	270	28	49
	84	276	32	49
	85	252	33	49
193/21	86	2250	11	40
	87	2250	12	40
	88	2250	13	40
	89	1800	13	40
	90	5490	25	40

Table 8 (continued)

Order	Jobs	Volume of job (VOL_n)(lts)	Bottling date (v_n)	Arrival date at port (s_n)
	91	5400	27	40
	92	3600	27	40
	93	4500	33	40
194/21	94	6075	36	42
	95	6075	36	42
	96	4500	36	42
	97	7362	39	42
	98	288	42	42
195/21	99	3600	19	21
	100	3600	19	21
	101	2250	20	21
	102	2250	20	21
	103	2250	20	21
	104	1350	20	21
196/21	105	2250	12	34
	106	4500	13	34
	107	2925	21	34
	108	12,487.5	22	34
	109	2925	25	34
	110	6727.5	25	34
	111	5760	26	34
	112	3375	26	34
197/21	113	13,500	18	34
	114	6300	19	34
199/21	115	855	18	49
	116	30	21	49
201/21	117	1575	25	35
	118	1575	27	35
202/21	119	2250	33	35
	120	9000	33	35
	121	4500	34	35
	122	2250	34	35
203/21	123	2511	34	35
	124	2511	34	35
	125	2511	34	35
	126	2511	35	35
	127	2511	35	35
	128	2511	35	35
207/21	129	513	18	39
	130	3078	21	39
	131	1026	26	39
	132	648	28	39
	133	513	33	39

Parameters data

See Tables 9, 10.

Table 9 Parameters data of the illustrative example

Fixed cost for using truck	5,000 [CLP]	Number of trucks	3
Unit inventory cost at port	50 [CLP]	Truck capacity	170 ls per truck
Unit inventory cost at winery	30 [CLP]	Bottling line capacity	200 ls per line
Fine for non-delivery of order	1,000,000 [CLP]		

Table 10 Parameters data of the case study

Fixed cost for using truck	600,000 [CLP]	Number of trucks	5
Unit inventory cost at port	$7.5	Truck capacity	14,175 ls per truck
Unit inventory cost at winery	$2.5	Bottling line capacity	21,800 ls per line
Fine for non-delivery of order	100,000,000 [CLP]		

Full experimental results

See Table 11.

Table 11 Experimental results for 10 instances of each experiment

IP		GH		IH		IH reduced		IH one shot	
Value	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)
2 Orders with 5 jobs each									
0	0.46	0	<<1	0	0.23	0	0.13	0	1.28
0	0.66	28	<<1	0	1.04	28	0.06	7	0.85
0	0.82	0	<<1	0	0.30	0	0.09	0	0.75
0	6.50	20	<<1	0	4.22	20	0.06	20	0.64
0	2.77	0	<<1	0	0.22	0	0.04	0	3.33
0	0.46	0	<<1	0	0.28	0	0.08	0	1.38
0	0.39	0	<<1	0	0.20	0	0.04	0	0.26
0	7.34	25	<<1	0	0.72	0	0.15	0	0.14
0	12.95	0	<<1	0	0.37	0	0.05	0	41.21
0	1.16	25	<<1	0	0.49	1	0.18	3	0.14
3 Orders with 5 jobs each									
0	66.19	20	<<1	0	57.70	20	0.44	20	38.11
0	64.03	9	<<1	0	37.00	9	0.10	9	1.88
0	56.42	8	<<1	0	44.70	8	0.45	8	7.35

Table 11 (continued)

IP		GH		IH		IH reduced		IH one shot	
Value	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)	Value (%)	Time (s)
0	550.41	17	<<1	0	140.30	17	0.15	17	62.54
0	15861.48	25	<<1	0	80.20	0	0.32	0	1.03
0	78.13	12	<<1	0	70.20	12	0.10	1	1.00
0	58.78	22	<<1	0	74.90	22	0.10	22	1.93
0	298.66	23	<<1	0	67.70	23	0.26	19	1.18
0	6.11	22	<<1	0	4.20	22	0.09	22	0.67
0	53.55	21	<<1	0	30.70	21	0.10	0	5.28
4 Orders with 5 jobs each									
0	45.75	17	<<1	0	32.40	17	0.19	17	61.36
0	173.48	13	<<1	0	93.10	13	0.53	13	30.06
0	71.13	15	<<1	0	80.30	12	0.33	0	0.38
0	177.36	24	<<1	0	100.88	15	1.70	15	0.22
0	49.34	27	<<1	0	102.48	27	0.30	16	0.57
0	72.23	23	<<1	0	115.04	23	0.45	23	34.14
0	3195.25	32	<<1	0	146.07	32	0.19	5	3.72
0	424.45	32	<<1	0	227.07	23	0.27	23	0.18
0	160.80	32	<<1	0	158.60	28	5.91	24	0.21
0	23.44	48	<<1	45	65.31	48	0.48	45	62.01
5 Orders with 5 jobs each									
0	181.91	14	<<1	0	112.24	1	8.14	0	0.65
6*	86400.00	24**	<<1	6	341.34	9**	5.28	11**	0.37
0	1299.16	21	<<1	0	273.20	13	1.31	18	0.23
0	369.33	19	<<1	0	144.19	2	0.50	2	0.26
0	2714.52	17	<<1	0	251.02	17	0.46	9	0.31
0	317.92	30	<<1	0	151.66	15	3.99	21	0.50
0	695.16	15	<<1	1	269.20	15	2.13	11	1.27
0	8864.14	12	<<1	0	135.52	12	0.37	10	61.30
12*	86400.00	24**	<<1	3**	179.74	24**	3.05	14**	0.26
0	65864.60	25	<<1	0	139.24	25	0.72	14	0.09

* Best GAP after one day of running CPLEX

** GAP computed using the best lower bound returned by CPLEX after one day of computation

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Declarations

Conflict of interest The authors declare no conflict of interests.

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