Downstream Oil Products Distribution Planning: A Portuguese Case Study

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Abstract In the actual worldwide environment, the oil industry faces fierce and growing competition. In this context, oil supply chains should be studied in order to improve their efficiency, while remaining flexible to successfully handle certain types of contingencies, such as lack of products or fleet unavailability. At the distribution level, tankers are commonly used in the downstream activities to transport the derivative products from distribution centres to service stations, comprising the secondary distribution level. This operation is usually short-term scaled to meet final consumers' demand. However, the availability and proper sizing of a fleet to perform the required distribution can be a complex problem due to the fact that demand is known on short notice and the distribution network may include hundreds of demand points to be satisfied. In this chapter, the T2S.opt—Tank to Station Optimizer—decision support tool is presented. T2S.opt addresses the fleet distribution planning problem under normal and abnormal operational scenarios. The optimal planning covers short-term solutions and minimizes operational costs. A Mixed-Integer Linear Programming (MILP) was developed and implemented to be used through a proper user interface, giving origin to T2S.opt. The software was used to schedule the secondary distribution of oil products of GalpEnergia in Portugal.

Keywords Oil supply chain · Downstream · Secondary distribution · Planning · Mixed-integer linear programming

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1 Introduction

In the actual worldwide environment, the oil industry faces fierce and growing competition. In this context, oil supply chains should be analysed in order to improve their efficiency, while remaining flexible to successfully handle certain types of contingencies, such as lack of products or fleet. At the downstream secondary distribution level, tankers are commonly used, due to their flexibility to transport the derivative products from distribution centres to service stations (MirHassani 2008). This operation is usually short-term scaled so as to meet final consumers' demand. However, the availability and proper sizing of a fleet to perform the required distribution can be a complex problem due to the fact that demand is known on short notice and the distribution network may include hundreds of demand points to be satisfied.

The optimal fleet allocation solution would require a Vehicle Routing Problem (VRP), or one of its variants such as the Capacitated VRP, to be solved in short periods of time over a geographically large area with several demand locations (service stations country wide or region wide). This problem is known to be NP hard and even small instances are difficult to solve. Since this is a daily exercise for many distribution companies, other approaches are required. On the other hand, real world tools used to this end usually are based on geographic knowledge and experience of schedulers to perform such allocation. The gap between an optimal distribution planning tool and what is currently used in companies leaves the opportunity for the academic community to focus on feasible and good solutions in short scheduling periods. Moreover, decision support tools using such type of solutions are of great support when dealing with different types of operational contingencies.

In this work we present a decision support system (DSS), named Tank-to-Station Optimizer (T2S.Opt), which addresses the fleet distribution planning problem under normal and abnormal operational scenarios. The system in study considers a network of oil products distribution centres that supply service stations on a daily basis. Distribution centres are supplied from refineries. The DSS is built so as to consider the distribution operation over a short-term time horizon (one to few days) minimizing operational costs. This DSS uses a MILP model which is solved with a free solver (GLPK). The DSS includes a user interface and a flexible architecture that can be fully customized, and uses the MILP-based solution strategy reported in Mota (2012). The proposed methodology is tested in a real world case study of a Portuguese company—GalpEnergia—which distributes oil products nationwide.

In the following section a literature review in the field of oil supply chains is presented. Section 3 describes the proposed mathematical model and a brief overview of T2S.opt. Section 4 presents the case study as well as the results obtained by using T2S.opt. Finally, Sect. 5 encloses the conclusions and future work.

2 Literature Review

The oil supply chain is commonly classified under three main segments: upstream, midstream and downstream. The first one encompasses the crude oil exploration and transportation up to refineries, the midstream involves the refining operations and lastly the downstream segment is concerned with the physical distribution of oil products to an extensive and diverse retail sector or to the petrochemical industry (An et al. 2011).

The transportation operations that take place throughout this supply chain may use diverse transportation types, as vessels, train, truck or pipelines. Vessels, sometimes even reaching VLCC—Very Large Crude Carriers—sizes, are used in crude transportation. Inland supply may also require either pipelines or train, depending on the quantity, distance and frequency of supply. On the downstream side, the distribution is usually broke down to primary and secondary (Fig. 1), where distribution centres (or depots) play a central role in managing oil products. Mainly in the secondary distribution level, trucks play a central role due to their enhanced performance in milk run type distribution. The remaining transportation modes are more frequent in the primary distribution level.

Pipelines have been extensively used in the oil supply chain over the last 40 years. Despite the initial investment, their operational cost is reduced when compared to other transportation types (Relvas et al. 2006; Herrán et al. 2010). In alternative, vessels are the most indicated for harbour connected nodes and large quantities (MirHassani 2008).

Planning in a supply chain might be different according to several aspects as performance measures and decision variables change and dependent on the business. According to An et al. (2011), five planning levels may be distinguished: strategic, tactical, operational, integration of tactical and operational, integration of strategic and tactical. Gayialis and Tatsiopoulos (2004), among other authors, chooses to distinguish only the first three levels of planning mentioned above.

Strategic planning uses aggregated information and regards long term decisions as investments and dimensioning of the logistics network. This may include locating and determining the capacity of the depots, physical flows, sourcing strategy, among other decisions (Gayialis and Tatsiopoulos 2004). The objective

Fig. 1 Downstream oil supply chain

functions are normally related to costs and flexibility of the network that is being modified or created (see Mota 2012).

Tactical planning regards medium-term decisions as inventory levels, production planning and distribution related to an existing network. The objective functions normally take into consideration the costs (or profit) and the responsiveness to the customer.

Operational planning considers detailed information and short-term decisions, such as daily repetitive operations, and concentrates in optimizing specific points of the network (Gayialis and Tatsiopoulos 2004). It may include transportation scheduling, detailed resource allocation, production decisions or distribution and routing problems as the vehicle routing problems and its variants (see Mirabi et al. 2010; Nussbaum et al. 1997). Typically, these types of problems are NP hard to solve and heuristics are proposed to solve them (see Mirabi et al. 2010).

The integration of the strategic and tactical models typically handles tactical decision variables, such as production and/or distribution scheduling, levels of inventory, and strategic decisions, like physical allocation, sizing infrastructures and/or transports, among others (Mota 2012). These models focus more in the downstream operations (An et al. 2011).

The integration of operational and tactical models, when compared with operational models, tend to include more than one operation and are more concentrated in the production activity (see Timpe and Kallrath 2000; Al-Othman et al. 2008). Given the focus of the present work, the integration of these two planning levels will allow to answer to our main research questions. However, most of the literature relies in normal operation scenarios and few methods are available to address contingency planning in distribution scenarios.

There are several approaches that can be used when dealing with uncertainty, risk and subsequent reactive planning. Uncertainty is related to the non-deterministic character of the variables under scrutiny.

Although it is generally consensual that planning taking into account uncertainty or adopting risk management strategies might bring considerable benefits, there are few approaches applied to the oil supply chain. Adhitya et al. (2007) propose a framework based on a rescheduling heuristic strategy to manage failures in a refinery. However, the oil supply chain may face numerous uncertainty factors or abnormal scenarios. To this end, decisions at different levels may be implied when finding solutions for these situations.

Real world downstream distribution scenarios have to cover several customer locations sourced from different refineries or distribution centres. Furthermore, under non-regular scenarios (e.g. lack of stock of a given product) tactical decisions related with allocation of customers to sourcing locations may arise at the operational level. Therefore, our aim is to develop a problem representation where the tactical level is integrated with the operational level of decision, where two major decisions are to be defined: allocation of customer locations to sourcing nodes and number of supply vehicles to be shipped from sourcing nodes.

3 Problem Definition

The problem in study consists of a distribution network with multiple depots and refineries. Each refinery supplies several depots with the respective products. The number, location and product availability of the depots are known. A fleet of trucks with different capacities and limited availability per truck type is used to transport the products from depots to customers (e.g. municipalities). In this way, either single customers or aggregated customers may be dealt within the proposed formulation. The time required to travel between network points (from depots to customers) is also deterministic and known. Each truck cannot visit multiple regions in one trip. This is mainly due to safety constraints in the routing of vehicles loaded with oil derivatives when they have to visit more than one customer location. Since stability issues may arise, frequently only one customer is visited or a restricted number of customer that are located within a short distance. Thus, the problem at hand differs from capacitated VRPs since the focus is customer allocation and demand fulfilment and fleet capacity planning.

Given this setting, we aim to determine the optimal distribution planning of refined products from depots to customers in short-term time horizons that minimizes distribution costs, which include transportation costs. Penalties for unmet demand are also accounted for.

3.1 Mathematical Formulation

The proposed solution is divided in two phases. In the first phase we aim designing the delivery routes from a depot to customers at a minimum cost. In case it is not possible to meet all the demand, due to fleet or/and product constraints, a second phase returns the minimum time that it would be required to supply that demand. Basically, the second phase problem has no fleet limitations.

The proposed formulation uses the following notation consisting of indexes, sets, parameters and variables.

Indexes:

i Depots;

j Customers;

k Products;

p Tankers;

t Time periods;

Sets:

$i \in I$ Set of all depots;

$j \in J$ Set of all customers;

$k \in K$ Set of products;

$p \in P$ Set of tankers;

$t \in T$ Set of time periods;
$R_{k,p}$ Set that relates products with tanker to transport it;
$S_{k,p,i}$ Set that relates products with tankers and depots;

Parameters:
$A_{i,k,t}$ Initial inventory of product k, at depot i, at time t (m^3);
$C_{i,j}$ Unitary distribution cost between depot i and customer j (€);
$Cam_{i,t,p}$ Available shifts from tanker p, in depot i, at time period t;
$Dem_{j,k,t}$ Demand of customer j of product k at time period t (m^3);
$IF^{min}_{i,k,t}$ Minimum inventory of product k, in depot i, at time period t (m^3);
$IF^{max}_{i,k,t}$ Maximum inventory of product k, in depot i, at time period t (m^3);
$Min_{i,j}$ Travelling time between depot i and customer j (h);
M Big-M number related with the order of magnitude of variable $Y_{i,j,k,t}$;
Pen Penalty per unit of volume not transported between depot i and customer j (€), defined as $Pen > MaxC_{i,j}$;
$TP_{i,t}$ Maximum flow from depot i at time period t (m^3);
$TR_{i,k,t}$ Refinery flow to depot i, from product k, at time period t (m^3);
V_p Transportation capacity of tanker p (m^3);

Non-negative Variables:
$X_{i,j,k,t}$ Flow of product k transported from depot i to customer j at time period t;
$Xn_{j,k,t}$ Demand of product k from customer j not satisfied at time period t;
$IF_{i,k,t}$ Final inventory of product k, in depot i at time period t;
$Y_{i,j,k,t}$ Demand of product k from customer j satisfied in the second phase and allocated to depot i at time period t;
$Yn_{j,k,t}$ Demand of product k from customer j not satisfied in the second phase at time period t;

Integer Variables:
$n_{i,j,t,p}$ Number of vehicles from depot i to customer j, from tanker p, at time period t;

Mathematical Model—1st Phase:

$$\text{Min } Z = \sum_t \sum_k \sum_j \left(\sum_i (C_{i,j} \times X_{i,j,k,t}) + Pen \times Xn_{j,k,t} \right) \tag{1}$$

$$Xn_{j,k,t} = Dem_{j,k,t} - \sum_i X_{i,j,k,t}, \quad \forall j, k, t \tag{2}$$

$$\sum_j \sum_k X_{i,j,k,t} \le TP_{i,t}, \quad \forall i, t \tag{3}$$

$$A_{i,k,t} + TR_{i,k,t} - \sum_{j} X_{i,j,k,t} = IF_{i,k,t} \quad t = 1, \forall i, k \tag{4}$$

$$IF_{i,k,t-1} + TR_{i,k,t} - \sum_{j} X_{i,j,k,t} = IF_{i,k,t} \quad t > 1, \forall i, k \tag{5}$$

$$\frac{\left(\sum_{k} X_{i,j,k,t}\right)}{V_p} = n_{i,j,t,p}\, \forall (k,p) \in R_{k,p}, \quad \forall j, t, I \tag{6}$$

$$\sum_{i} \sum_{j} (n_{i,j,t,p} \times Min_{i,j}) \leq Cam_{i,t,p}\, \forall (k,p,i) \in S_{k,p,i},\ \forall t \tag{7}$$

$$IF_{i,k,t}^{min} \leq IF_{i,k,t} \leq IF_{i,k,t}^{max}, \quad \forall i, k, t \tag{8}$$

$$IF_{i,k,t}, X_{i,j,k,t}, Xn_{j,k,t} \geq 0, \quad n_{i,j,t,p} \in \mathbb{N}, \quad \forall i \in I, \forall j \in J\ , \forall k \in K, \forall t \in T \tag{9}$$

The objective function (1) minimizes the transportation costs between depots and customers (first term), as well as the penalties in case of unsatisfied demand (second term).

Equation (2) acts as a soft constraint that determines unmet demand. Equation (3) limits throughput of each depot in each time period. Equation (4) defines the final inventory at the beginning of the time horizon and Eq. (5) the final inventory for the subsequent time periods. Equation (6) ensures that the cargo transported by one vehicle type (and taking into account the product to be transported) is a multiple of the capacity of that type—due to safety conditions for the transportation. Equation (7) constraints the fleet transportation capacity, given different trucks (or tanks) and depots. Constraints in Eq. (8) limit the product inventory per depot and time period. Finally, Eq. (9) is a non-negativity constraint for flows and inventory.

Mathematical Model—2nd Phase:

$$\text{Min } Z = \sum_{t} \sum_{i} \sum_{j} \sum_{p} \left(Min_{i,j} \times n_{i,j,t,p}\right) + \sum_{t} \sum_{k} \sum_{j} \left(M \times Yn_{j,k,t}\right) \tag{10}$$

The second phase returns as a solution what are the fleet requirements to meet unfulfilled demand of the first phase. In this case, the objective function minimizes the required time to fulfil the new demand (first term), by allocating the unmet demand of the 1st phase to new depots, as well as it minimizes the penalties when such allocation is not possible (second term).

$$Yn_{j,k,t} = \sum_{i} Y_{i,j,k,t} - Xn_{j,k,t} \quad \forall j, k, t \tag{11}$$

$$\mathrm{IF}_{i,k,t} \geq \sum_{j} \mathrm{Y}_{i,j,k,t} \quad \forall i, k, t \tag{12}$$

$$\sum_{j} \sum_{j} \mathrm{Y}_{i,j,k,t} \leq \mathrm{TP}_{i,t} - \sum_{j} \sum_{k} \mathrm{X}_{i,j,k,t} \quad \forall i, t \tag{13}$$

$$\frac{\left(\sum_{k} \mathrm{Y}_{i,j,k,t}\right)}{\mathrm{V}_{p}} = \mathrm{n}_{i,j,t,p} \quad \forall (k,p) \in \mathrm{R}_{k,p}, \forall j, t, I \tag{14}$$

$$\mathrm{Yn}_{j,k,t}, \mathrm{Y}_{i,j,k,t} \geq 0, \quad \mathrm{n}_{i,j,t,p} \in \mathbb{N}, \quad \forall i \in I, \forall j \in J, \forall k \in K, \forall t \in T \tag{15}$$

Equation (11) allocates the unmet demand $\mathrm{Xn}_{j,k,t}$, calculated in the 1st phase, to the nearest possible depot. Constraint in Eq. (12) ensures that there is sufficient inventory in the depots allocated in Eqs. (11) and (13) limits the throughput of each depot at time t. Equation (14) restricts the flow of products to the exact capacity of each tank. Finally, Eq. (15) is the domain definition constraint.

4 Case Study and Results

4.1 *Case Study Summary*

The object of this study consists of the downstream fuel distribution planning of four refined petroleum products: gasoline, diesel, heating oil (HO) and Jet Fuel (JF). This activity is performed by Petrogal, a subsidiary company of the Group GalpEnergia, from this point onwards referred as Galp.

The distribution activity includes six depots, as one can see in the Table 1 with different capacities and products being stored, which satisfy a total of roughly 270 Portuguese municipalities. Figure 2 illustrates depots' locations, as well as crude oil flow. The numbers presented in Fig. 1 illustrate the actual distribution regions covered by outsourced carriers.

The data used to test the proposed approach is referent to 2011.

Table 1 Average product availability by depot (m^3)

Depots	Gasoline	Diesel	HO	JF
Boa Nova	10,000	10,000	–	700
Real	–	400	10,000	–
CLC	10,000	10,000	–	10,000
Mitrena	800	800	10,000	–
Sines	10,000	10,000	–	1225
Aveiro	–	–	–	–

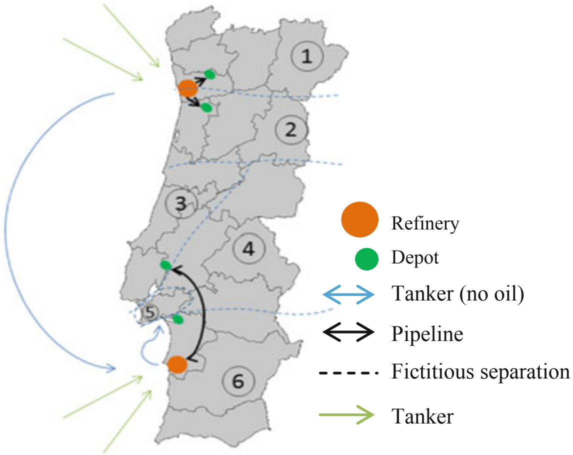

Fig. 2 Galp's simplified national supply chain

Within the six depots, Aveiro is not currently in use. In the case of Jet Fuel, Boa Nova stores typically around 700 m^3, Sines roughly 1225 m^3 and CLC has practically no fuel limitation.

The daily national consumption of gasoline, diesel and HO (aggregated consumption) in 2011 was analysed through a histogram map and the authors concluded that the most frequent consumption quantities are situated in the ranges of 0–6000 m^3/day and 8000–9000 m^3/day. Days with higher consumptions may reach volumes of 10,000–13,000 m^3/day, but with a frequency below to 20 %. The fuel transportation is outsourced to five carriers. These carriers are allocated to depots, and each carrier manages the amount of trucks to perform the transportation service. In the present scenario, Table 2 illustrates how many trucks are available per day in each depot (1 shift equals 8 h of transportation and some trucks perform 2 shifts per day).

The maximum capacities of each normal truck tank are 32 and 35 m^3 in the case of JF. Typically, the latter type of truck performs an average of 5 deliveries per day and the former an average of 3 deliveries.

The contingencies to which the distribution activity is exposed can be broadly categorized between absences of product or absence transport capacity. In the case of Jet Fuel there is a clear limitation of the carrying capacity given the scarcity of this type of truck.

Table 2 Daily trucks and shifts available by depot

	Trucks	Shifts	JF trucks	JF shifts
Boa N. + Real	51	78	(pipeline)	–
CLC Aveiras	40	49	9	18
Mitrena	6	9	–	–
Sines	20	34	(railway)	–
Aveiro	–	–	–	–

4.2 Case Study Results and T2S.Opt Decision Support Tool

The proposed mathematical models were implemented in the T2S.opt application. This application was developed to interpret model solutions in an effective and interactive way.

This application possesses a specific architecture, which integrates an Excel and Access file with the proposed open source optimization Solver GLPK. The Excel file is the user interface where several functionalities are available. The usage of this application will be exemplified in the results section, since all figures are generated by T2S.opt.

Several contingency scenarios were implemented in the T2S.opt application. The objective of the results presented is to determine the impact of closing any of the existing depots and the subsequent solution of reallocating the available fleet (where the depot was closed). First, we are going to present a normal distribution scenario in order to compare it with the contingencies referred. The closure of distribution centres will be illustrated with the examples of CLC and Sines.

4.2.1 Normal Distribution Scenario

This scenario contemplates an ordinary day of distribution. To fulfil 7048 m^3 of diesel, 2326 m^3 of gasoline and 64 m^3 of HO, the distribution operation consumes a total of 77,815 min, 47,076 km and a distribution cost of 118,890 €. In terms of JF, for a daily supply of 65 deliveries (2275 m^3) from CLC to the Lisbon airport, it requires 8515 min of transportation time and an expense of 32,258 € in transportation costs. The areas of influence of the five depots considered are shown in Fig. 3.

The illustrated areas are consistent with the current distribution scheduling. Thus, in contingency, these areas are expected to move in the direction of the closed depot, to minimize the unfulfilled demand.

4.2.2 Abnormal Scenario: Closure of CLC

This scenario includes the closure of CLC distribution centre. 71 % of the total demand was satisfied, which means that 2784 m^3 were unfulfilled. The regions whose demand was not satisfied are illustrated in Fig. 4a. In this scenario were consumed 57,221 distribution minutes and the total distribution cost was of 76,908 €. The unitary distribution cost was 11.55 €/m^3 transported, a 7.94 % decrease when compared with the normal distribution scenario.

However, one can minimize the negative impacts by reallocating the available fleet in CLC to the correct depots. Figure 4b, in the following figure, illustrates the impact of reallocating the non-used fleet. With the solution computed by the second phase of the mathematical model one allocated 5 shifts to Aveiro and 44 to Sines. This measure made the unsatisfied demand decreased 69 %, when compared to the

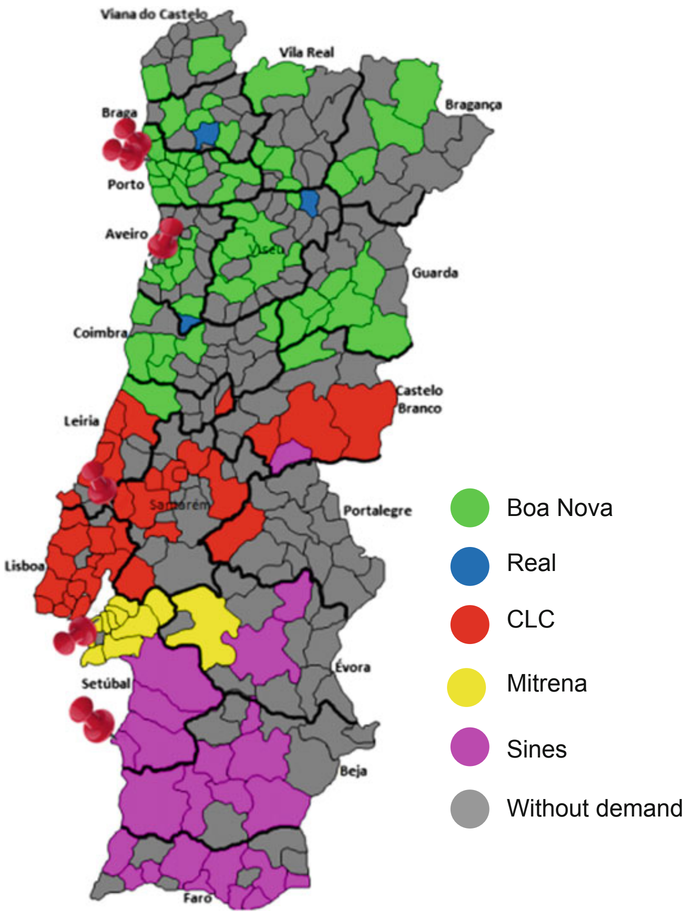

Fig. 3 Normal distribution scenario depot influence areas

scenario where no fleet was reallocated, to a total of 864 m^3. In this scenario the unitary cost of distribution increased 0.31 %, from 12.59 to 12.63 €/m^3.

4.2.3 Abnormal Scenario: Closure of Sines

This scenario includes the closure of Sines. 86 % of the total demand was satisfied, which means that 1312 m^3 were unfulfilled. Figure 5a shows the unsatisfied municipalities. In this case, 65,147 min were used for a total distribution cost of 107,108 €. This gives a unitary cost of 13.18 €/m^3 transported, a 4.67 % increase when compared with the normal distribution scenario.

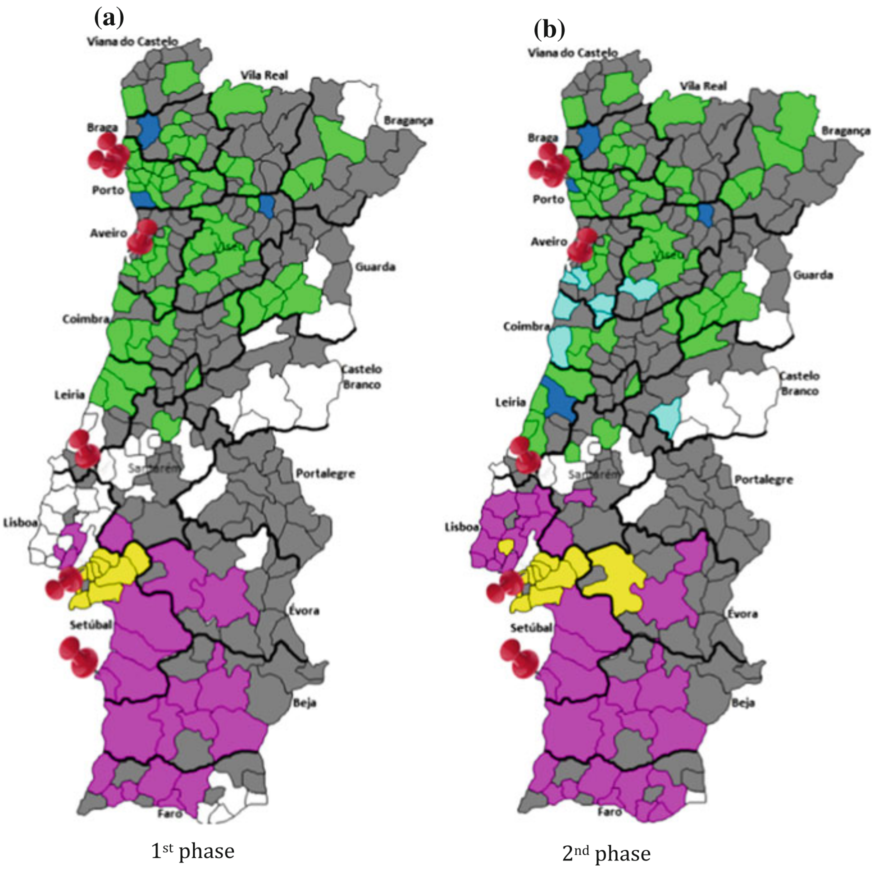

Fig. 4 Abnormal scenario: closure of CLC

In the reallocation scenario one considered 7 shifts in the Mitrena and 27 in the CLC. With this measure one decreased the unsatisfied demand to 384 m^3, a 71 % drop when compared with the no reallocation scenario. The unitary cost of distribution increased 10.64 %, from 12.59 to 16.01 €/m^3 (when compared with the normal scenario).

4.2.4 Abnormal Scenario: Fleet Unavailability

Correct contingency impact identification will not only allow us to clarify the most critical contingencies, as well as aligning the expectations and goals of the current programming team in the company in study. Typically, the most ordinary contingency is related to the lack of fleet. So we decided to study the impact of an unexpected 25 and 50 % fleet unavailability. The demand used in this study was the same of the previous sections.

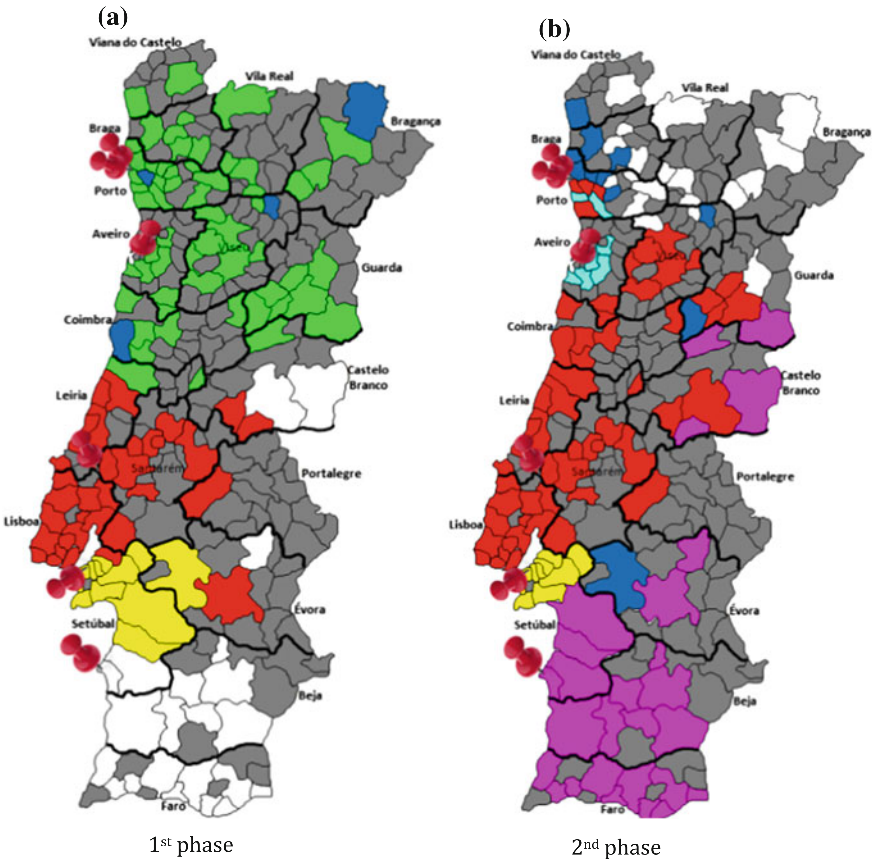

Fig. 5 Abnormal scenario: closure of sines

Table 3 Abnormal scenario fleet unavailability: impact of 25 and 50 % fleet unavailability

Scenarios	Unmet demand (m^3)	Shifts needed	U.C. of distribution (€/m^3)	U.C. of transport (€/m^3)
Normal	0	0	12.59	8.90
50 % Boa N.	960	35	11.82	8.01
50 % CLC	832	26	11.92	8.80
25 % Boa N.	320	14	12.26	8.57
50 % Sines	284	11	12.21	8.42
25 % CLC	256	11	12.27	8.89
50 % Mitre.	96	4	12.60	9.11
25 % Sines	64	3	12.50	8.80
25 % Mitre.	0	0	12.66	9.15

Table 3 summarizes each scenario impact. The first column introduces the scenario and the fleet's percentage drop in the respective depot. Subsequently, it is presented the amount of unmet demand per scenario, the shifts needed to fulfil the unmet demand and the unitary costs (U.C.) of distribution and transport.

As one can see, and in line with contingency scenarios previously studied, a drop of 50 % of the fleet in Boa Nova and CLC depots has serious consequences on the fulfilled demand. Note also that, for example Boa Nova, in order to supply the 960 m^3 of unfulfilled demand, it would require 35 additional shifts. That is, each delivery takes an average of 1.2 shifts, or approximately 9 h, to be performed. Another important fact is that the unitary cost of transportation, and distribution, is higher than the normal unitary costs only when there is unavailable fleet in the Mitrena depot. This means that longer distances have to be covered with origin in other depots to fulfil demand otherwise supplied by Mitrena depot.

4.2.5 Fleet Resize and Reallocation

In this section we propose an alternative to the current fleet configuration, by redistributing the available fleet. The goal is to increase savings and mitigate the current operational contingency potential of Galp's operation. For this purpose we are going to use the T2S.opt application.

In order to evaluate the best configuration that suits both goals we constructed a sample of 18 daily demands based in 2011s demand. For each, we calculated the optimum fleet allocation to depots, in terms of shifts, using the first phase of the mathematical model. Table 5 summarizes the results obtained, where the column named average (Avg.) represents the fleet configuration proposed as an average of the values obtained within the sample.

Comparing the results obtained with the current fleet configuration (5th column of Table 4) there is a positive 10 shift deviation (6th column). However, it was calculated a deficit of 4 shifts in Mitrena. In terms of distribution costs, the

Table 4 Fleet resize and reallocation results

Depot	Min.	Max.	Avg.	Now	Dev.
Boa Nova + Real	65	81	75	78	+3
CLC	36	45	41	49	+8
Mitrena	12	15	13	9	−4
Sines	25	38	31	34	+3
Total shifts	138	179	160	170	+10

Table 5 Daily cost comparison of fleet configurations

Costs	Actual config. (€)	Proposed config. (€)
Transport	82,854	83,335
Product	33,509	32,645
Total	116,363	115,980

Table 6 Computational results

Scenarios		Computational time (CPU s)		Relative gap (%)	
		1st Ph.	2nd Ph.	1st Ph.	2nd Ph.
Normal	Average	758.9	0.1	0.0	0.0
	Maximum	2901.5	0.1	0.0	0.0
	Minimum	1.3	0.1	0.0	0.0
Contingency	Average	12,953.9	0.1	1.0	0.0
	Maximum	47,945.5	0.1	5.1	0.0
	Minimum	184.4	0.0	0.0	0.0

proposed configuration represents an average daily gain of 383 € in relation to the current configuration.

The decomposition of the average distribution costs for the current fleet and for the proposed fleet scenario is presented in Table 5.

As one can see, both alternatives to the current fleet configuration represent an improvement in the average distribution costs.

4.3 Computational Results

Both models were implemented using the programing language of GUSEK and solved in an Intel® Core(TM)2 Duo with 2.67 GHz and 4 GB RAM computer, using GLPK solver. The stopping criteria are either the optimal solution determination or reaching the memory limit.

Table 6 resumes computational data in two categories, normal distribution scenarios and contingency scenarios, in average terms, for the sake of simplicity.

One can conclude that the computational effort varies significantly with the scenario being tested in the first model phase. However, contingency scenarios, which are more restrictive, tend to consume more time and maintain higher relative gaps.

The first phase of the model is characterized by 21,360 variables, 6405 are integer variables, and 8631 equations. The second phase is characterized by 21,360 variables, 6405 are integer variables, and 8605 equations. This model size is applicable to all scenarios, which consisted in a single day of time horizon (one time period).

5 Conclusions and Further Work

This paper proposes a decision support tool, based in an exact model that aims at minimizing operational costs of the secondary distribution operation. The solution procedure includes a MILP model solved using a free solver—GLPK—and managed through a user interface, the T2S.opt application.

The proposed MILP model allows the integration of tactical and operational decisions, such as the determination of areas of influence per distribution centre (frequently a tactical decision) and the daily distribution planning (operational decision). This model flexibility allows obtaining a solution to support the distribution operation decisions even when abnormal scenarios occur (as stated, lack of product or lack of fleet) as well as for fleet sizing (tactical decision).

A current limitation of the proposed mathematical models lies in the fact that a vehicle is only able to perform one delivery per trip. The introduction of a condition, in future developments, that allows freight to make more than one delivery per truck will enable more accurate and real results.

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