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## Computing Dynamic Routes in Maritime Logistic Networks

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# Computing Dynamic Routes in Maritime Logistic Networks

Hervé Mathieu, Jean-Yves Colin and Moustafa Nakechbandi

## Abstract

In this paper, we study the problem of finding the path that maximizes the gain toward one of several destination ports subject to uncertain information on the expected gain in each port. Although the cost of a ship trip between two points is usually predictable, some events may happen, thus impacting the cost. The price of goods to be delivered may fluctuate during the trip (thus impacting the gain), or the price to pay at the destination point can be higher than expected (in case of a strike for example). All of this has important economical consequences for the ship-owner and for the port on a long-term basis. In this context, it is important for a ship-owner to be able to react quickly when a destination port is no longer available. When a port terminal is on strike for example, ships are rerouted to other ports to be loaded and unloaded. We propose in this paper a simple and yet efficient algorithm to re-compute the path of the ship, when she is on the way, based on the computation of the longest path in a weakly dynamic graph, in order to maximize the global gain of the trip.

**Keywords:** dynamic graph, longest path problem, maritime network, route planning, time and costs factors.

## 1. Introduction

Static graphs have a long history of being used to efficiently represent static problems. In these problems, all the data are known from the start. The real world is not static, however, and the solutions to static problems may not always be used (Alivand, Alesheikh and Malek, 2008). Some data may change, or be unknown in advance. For example, the traversal duration of a location may depend on traffic density, the presence or not of traffic jams, work in progress, etc. that are all time dependent and usually hard to predict. Thus several approaches have been proposed to study parametric graphs (Ahuja, Magnanti and Orlin, 1993) and dynamic graphs (Boria and Paschos, 2011).

Fully dynamic algorithms, for example, are applied to problems that can be solved in polynomial time. They start with a computed optimal solution, and then try to maintain it when changes occur in the problem. They often propose sophisticated data structures to reach this goal (Demetrescu and Italiano, 2004). When the delay between a change and the moment a new solution is needed is very small, or when the problem itself is NP-hard, faster algorithms are needed. These re-optimizing algorithms usually start from an initial solution that is not optimal but is expected to be of good quality, if possible. As soon as a change is detected, they compute a new solution, trying to do it faster than classical algorithms. Or they compute a new solution as quickly as the classical algorithms but this resulting solution is better than the ones found by classical algorithms. These algorithms include meta-heuristics such as ants colony algorithms (Balev, Guinand and Pigné, 2007), or swarm algorithms (Bajgan and Farahani, 2012). Another approach used is probabilistic. Probabilities are associated to some variables in the graph, such as the value of a weight, or the presence of a node or of a constraint, for example. The algorithms used in these problems usually compute a solution and then do some robustness analysis in the probability space (Fulkerson, 1962). Or they do a quick re-optimization of the solution once the parameters of the problem are perfectly known (Bertsimas, 1988; Jaillet, 1985).

In this paper, we study route planning in a maritime network (Joly, 1999). More specifically, we study the problem of finding the most interesting path toward one of several destination ports subject to uncertain information on the expected gain in each port. Although the cost of a ship trip between two points is usually predictable, some events may happen, thus impacting the cost. However, in most cases, only the final part of the trip is subject to change. The price of goods to be delivered may locally fluctuate during the trip (thus impacting the gain), or the price to pay at the destination point can be higher than expected. For example, it may happen that the dockers of a maritime port are on strike (examples of strikes include Le Havre-Rouen-Marseille 2008, Liverpool between 1995 and 1998 also known as Liverpool's Dockers' strike, Rotterdam 2013). Actually, the strike phenomenon in maritime ports happens on a regular basis all over the world. To have an idea of the strike impact on maritime traffic, we can quote the example of the Greek port of Piraeus : Piraeus' volume peaked at 1.6 million TEU (Twenty feet Equivalent Unit) in 2003, but strikes and unrest led to a throughput of only 433,000 TEU in 2008 (Notteboom, 2013). Moreover, "exceptional" events can make a destination port unavailable: bombing, blockade because of economical sanctions etc. It is then necessary to reroute a ship when its destination port is unavailable as soon as possible (Hamburg South Terminal, 2013). All of this has important economical consequences for the ship-owner and for the port on a long-term basis. Thus, when a merchandise ship has to stay docked in a port without being taking care of, it implies a money loss that can be important for the ship-owner: sailors' wages, ship rental, blocked merchandise, disrespect of deadlines for merchandise delivery (penalties), and extra fuel consumption. In this context, it is important for a ship-owner to be able to react quickly when a destination port is no longer available.

## 2. Problem Statement

Maritime Shipping Graph (MSG): To study this problem, we will consider a graph  $G = (V, E)$ .  $V$  is the set of nodes,  $V = S \cup P \cup \{D\}$ ,  $S = \{1, 2, \dots, s\}$  is the set of stable nodes,  $P = \{X_1, X_2, \dots, X_p\}$  is the set of non-stable nodes (representing destination ports) and  $D$  is the destination node.  $E$  is the set of edges, and to each edge is associated a weight  $w \in \mathbb{R}$ . All the edges between a node of  $S$  and any other node are stable and their negative weights, that represent costs, never change. There is no edge between a stable node and  $D$ . However all edges leading to the final destination  $D$  in the graph are not stable and their weights may change at any time. The  $X_i$  nodes indicate the various ports available for delivery, and  $D$  is an added node indicating the abstract delivery of the load. Each edge between a node  $X_i$  and node  $D$  is non-stable and has a value  $x_i$ , representing the current expected profit for delivering the load in port  $X_i$ . We call this graph a MSG, Maritime Shipping Graph (see figure 1).

The length of a path is the sum of the weights of its edges. Longest paths that do not include any variable edge may be computed with the Dijkstra algorithm.

For example, taking the simplistic example of a wheat cargo, starting from Argentina to Europe, it may pass through several points (such as the Horn Cap or the Panama Canal). The price to pay, in oil, time, fees and such is usually known and may be represented by a simple static graph. Once the ship is close to Europe, each possible port will have different and possibly changing profit due the local conditions (port availabilities, adding the cost of train or road transports, strikes...). The profit earned  $PE$  considered is:

$$PE = SP - LF - TC$$

with  $SP$  being the selling price at final destination,  $LF$  being local fees and expenses at final destination, and  $TC$  being travel costs to Europe.

For example on the graph of Fig. 1, starting from node 1, we intend to reach one of the final ports  $X_1$ ,  $X_2$  or  $X_3$ . The profit expected from port  $X_i$  will be the price received for the cargo minus the cost to deliver it, minus the cost to go to the port.



weights change, new optimal paths may directly and immediately be deduced and used without any further re-computations.

The LPP we study will use the model illustrated on Fig. 1. Each stable value is a negative value representing its cost, and the non-stable value of this kind of weakly dynamic graph is the price received for the cargo minus the miscellaneous local costs (including the effects of strikes, if any.)

### 3. Main results

#### 3.1 The proposed algorithm

We present now the following algorithm to solve this problem:

**Algorithm**

**Input:**  $G=(V, E)$  is a MSG, with  $P$  being the subset of non stable nodes, and  $D$  being the destination

**Output:** longest paths  $LP(j, D)$  from any node  $j$  of  $G$  to  $D$

**For** each non-stable node  $X_i$  of  $P$  do

Compute  $LPS(X_i)$  = set of longest paths that do not use a variable edge, from all nodes  $j, j \in V - \{D\}$  to node  $X_i$  using the reverse Dijkstra algorithm.

Let  $d_{X_i[j]}$  = the length of the path in  $LPS(X_i)$  that starts from  $j \in V - \{D\}$  of the graph.

**End For**

The longest path  $LP(j, D)$  from  $j$  to  $D$  is the path such that  $\text{length}(LP(j, D)) = \max(d_{X_i[j]} + x_i, X_i \in P)$

### 3.2 Example: We now apply the algorithm on the graph of Figure 1

The least costly distance from each stable node to each non-stable node is presented in Table 1.

Stable node to non stable node	X1	X2	X3
1	-40	-70	-65
2	-30	-60	-65
3	-50	-55	-45
4	-65	-65	-55
5	-20	-30	-35
6	-40	-25	-15

Tab. 1: distances from all stable nodes to all non stable nodes

For example, the value of the least costly path from node 3 to go to node X1 is -50, to go to node X2 is -55 and to go to node X3 is -45.

We now suppose that the current expected profits at the possible delivery ports are  $(x_1, x_2, x_3) = (1000, 1100, 1200)$ .

The length of the longest path (that is the one with the highest total profit) from node 3 to D is  $\max(1000 - 50, 1100 - 55, 1200 - 45) = 1155$ . From node 3, the longest path will go to port X3 for delivery in the current conditions.

Now, if  $x_3$  falls to 1050 and the other values do not change, then the length of the longest path from node 3 to node D is  $\max(1000 - 50, 1100 - 55, 1050 - 45) = 1045$ . From node 3, the longest path will go to port X2 for delivery in these new conditions.

### 3.3 The proposed algorithm

Theorem 1: Let  $G=(V, E)$  be a Maritime Shipping Graph, and  $\{x_i, \text{ with } X_i \in P\}$  be the values of the non stable edges. Let  $dX_{ij}$  the longest path without non stable edges from a stable node  $j$  to  $X_i$ ,  $X_i \in P$ . Then the length of the longest path from a node  $j$  to node D is  $\max \{ dX_{ij} + x_i, \text{ with } X_i \in P \}$



Theorem 2: The complexity of the algorithm is  $O((m + n \log n)p)$  with  $n$  being the number of nodes,  $m$  the number of edges and  $p$  the number of non stable nodes. One interesting use of this result is in the building of pre-computed parametric routing tables. These parametric routing tables include critical conditions that can easily be used to establish very quickly a new destination if the expected profit in any possible final destination crosses a computed threshold value.

We call critical conditions of a given node, the set of length functions associated to the longest paths to this given node computed by the algorithm. Because the functions of this set are constants, or very simple linear functions of the non-stable weights, they can be computed and compared very easily. Thus for each target node, the set of alternative paths can be stored along with the associated set of critical conditions. As soon as any variable weight changes, the critical conditions of the target node just need to be re-computed and compared. Then the new longest path may be chosen among the alternative paths stored for this node. No re-computation of longest paths is needed, no data beside the current values of the variable edges need to be exchanged, and all decisions may be taken locally.

The result found by the proposed algorithm can then be used to build alternative routing tables for each ship starting from any location of the graph. The same tables can then be used to route these ships to the most profitable destination at any time during its journey.

We develop the above ideas in the next part, using the example of Fig. 1.

## 4. Developed Example

We now again use the example of Fig. 1 with the current values  $(x_1, x_2, x_3) = (1000, 1100, 1200)$  for the current non-stable weights. Applying the algorithm gives the distances, from all nodes to D, presented in the right part of Table 2:

	X1	X2	X3	Distance to D using (X1, D)	Distance to D using (X2, D)	Distance to D using (X3, D)	Best distance to D if (x1, x2, x3)= 1000,1100,1200
1	-40	-70	-65	x1-40	x2-70	x3-65	1135
2	-30	-60	-65	x1-30	x2-60	x3-65	1135
3	-50	-55	-45	x1-50	x2-55	x3-45	1155
4	-65	-65	-55	x1-65	x2-65	x3-55	1145
5	-20	-30	-35	x1-20	x2-30	x3-35	1165
6	-40	-25	-15	x1-40	x2-25	x3-15	1185
X1	0	-40	-50	x1	x2-40	x3-50	1150
X2	-40	0	-10	x1-40	x2	x3-10	1190
X3	-50	-10	0	x1-50	x2-10	x3	1200

Tab. 2: distances from all stable nodes to all non-stable nodes, and to D with  $(x1, x2, x3) = (1000, 1100, 1200)$

Now, for any node, the length of its longest distance depends on the values of the non-stable edges. The possible lengths are summarized in Table 3.

Next, it is now possible to build a parameterized routing table in each node to go to D. In the parameterized routing table of a given node, which neighbor to use depends on which part of the max formula gives the highest result using the current values of the non-stable edges. Table 4 presents the parameterized routing tables of nodes 3 and 4 if we have  $(x1, x2, x3) = (1000, 1100, 1200)$ . With these values, x3-55 in Table 5 at node 4 gives the highest result of 1145, so a ship at node 4 with the above conditions will go next to node 6.

We now start to compute the sensitivity of the result in each node, stable or not, only if one non-stable value changes. At node 1 for example, the best path to D has a length of 1135, and uses edge (X3, D) to D.

Node	Parameterized longest distance to go to D
1	$\text{Max}(x1-40, x2-70, x3-65)$
2	$\text{Max}(x1-30, x2-60, x3-65)$
3	$\text{Max}(x1-50, x2-55, x3-45)$
4	$\text{Max}(x1-65, x2-65, x3-55)$
5	$\text{Max}(x1-20, x2-30, x3-35)$
6	$\text{Max}(x1-40, x2-25, x3-15)$
X1	$\text{Max}(x1, x2-40, x3-50)$
X2	$\text{Max}(x1-40, x2, x3-10)$
X3	$\text{Max}(x1-50, x2-10, x3)$

Tab. 3: Parameterized longest distance to go to D

If current highest critical condition at node 3 is	Then go to neighbor node:
$x1 - 50$	5
$x2 - 55$	6
$x3 - 45$	6

Tab. 4: Parameterized routing tables of nodes 3 to go to node D,  $(x1, x2, x3) = (1000, 1100, 1200)$

If current highest critical condition at node 4 is	Then go to neighbor node:
$x1 - 65$	3
$x2 - 65$	6
$x3 - 55$	6

Tab. 5: Parameterized routing tables of nodes 4 to go to node D,  $(x1, x2, x3) = (1000, 1100, 1200)$

The second best destination port is X2, using edge (X2, D) to D, and has a length of 1030. The remaining possible destination is X1, using edge (X1, D) to D, and has a length of 960.

Now, for a different path to be chosen if only one non-stable value changes, two cases are possible. Either the profit at the best destination port falls so much that the second best becomes better, or the profit at one destination port that is not the best one climbs so much that it becomes the best one.

Comparing the values found in Table 2, and using the computed distance formula to go from any stable node to any non stable node, we can deduce that, at node 1 for example, the second best destination port becomes the best one if  $x_3 - 65 < 1030$ , that is if  $x_3 < 1095$ . We can also deduce that, at node 1, destination port X1 will becomes the best destination port if  $x_1 - 40 > 1135$ , that is if  $x_1 > 1175$ . And that, at node 1, destination port X2 will becomes the best destination port if  $x_2 - 70 > 1135$ , that is if  $x_2 > 1205$ .

We call these values (1175, 1205, 1095) at node 1 the critical values of node 1 for the prices at destination ports (X1, X2, X3) if  $(x_1, x_2, x_3) = (1000, 1100, 1200)$ . If any single profit change occurs from the initial conditions  $(x_1, x_2, x_3) = (1000, 1100, 1200)$ , then there will be no path change to consider if the new price is not above its critical value for a non best destination port, or is not below its critical value for the best destination port. Furthermore, if the local profit changes again many times whereas the other non-stable profits do not change, than there is no re-computation needed of any path and values.

## 5. Conclusion

In this paper, we studied the problem of finding the most interesting path (the one that maximizes the gain) toward one of several destination ports subject to uncertain information on the expected gain in each port and rerouting a ship when needed.

We proposed a simple and yet efficient algorithm to re-compute the path of the ship, when she is on the way, based on the computation of the longest path in a

weakly dynamic graph, in order to maximize the global gain of the trip. Parametric routing tables are pre-computed, and critical values are deduced.

As a final remark, one can note that a particular pathological classical situation that may arise in this kind of problem is that the expected values between two possible final destinations may change several times such that the ship must alternatively follow a path along and edge from A to B, then back from B to A, several time. It is a well-known problem of sensitivity in dynamic problems. One idea of heuristic may be that the ship is not allowed to come back toward another destination port unless the total expected profit there is superior to the total expected profit before the last change. With this heuristic, it is not possible for a ship to travel forever between two ports, because the prices will not increase forever.

In the future, we intend to study the problem of finding longest paths in weakly dynamic graphs when some non-stable edges are not close to the destination node (passing through the Suez Canal for example).

We also intend to work on extending this result to the problem of arbitraging multi-deliveries when a ship at one time or another must reach several destinations successively.

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