Decision making in a Dynamic Transportation Network: a Multi-Objective Approach

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Abstract: *Multiple different attributes are important in the container-to-mode assignment in a transportation network. This paper proposes an interactive multi-objective optimisation approach for planners of those transportation networks. This approach offers a range of solutions according to her/his preferences, and offers the opportunity to seek for new ones if the planner is not satisfied with the solutions found so far.*

Keywords: *Container Logistics, Minimum cost multi commodity flow, Space-time graphs, Multi-objective optimisation, Robustness, Flexibility*

1 Introduction

In this paper we look at a transportation system where logistic units (e.g., containers) travel freely through this network. Decision makers here can be logistic service providers, clients controlling the stream of their containers, intelligent containers or other smart logistic units themselves. This occurs in Physical Internet (PI) and in Synchromodal or Intermodal networks. For an overview of those concepts and differences we refer the reader to Ambra et al. (2019). Many transportation planning problems are solved via a deterministic optimisation-based tool where the lowest cost solution is chosen (Caplice and Jauffred (2014)). However, the used forecasts of the demand and transportation times can be very inaccurate and realisations may lead to drastically changed, or even infeasible plans. This changing of plans will become an important issue in realisation of synchromodal transportation networks. The Platform Synchromodality (www.synchromodaliteit.nl) provides the following definition: ‘Synchromodality is the optimally flexible and sustainable deployment of different modes of transport in a network under the direction of a logistics service provider, so that the customer (shipper or forwarder) is offered an integrated solution for his (inland) transport.’ Synchromodality is based on the usage of various transport modes available in parallel to provide a flexible transport solution, the entrustment to the logistics service provider with the choice of transportation mode and the possibility to switch in between transportation modes in real time, as can be seen in Agbo and Zhang (2017), Bahdani et al. (2016), and De Juncker et al. (2017). Especially the real time aspect, in combination with the need to make (some sort of) general planning, gives need for robust and flexible plans, where costs and customer satisfaction keep their importance.

In this work, we propose an interactive approach based on multi-objective optimisation, which is meant to be used as a decision support tool for a transportation planner. In most papers cost of the operation and service time are still the only used objectives, and other attributes are neglected (SteadieSeifi et al. (2014)). In Ishfaq and Sox (2010) it is proposed that cost, service, frequency, service time, delivery reliability, flexibility and safety are all performance indicators. The work in Ramezani et al. (2013) takes customer responsiveness and quality as objectives next to costs. We propose Robustness, Flexibility and Customer satisfaction as alternative objectives next to costs in the multi-objective approach.

The mathematical framework we use as basis in the approach is the *Multi-Commodity Flow problem* (Crainic (2000)), to model the sychromodal planning problem. In the case where only cost is considered, it can be modelled as a Minimum Cost Multi-Commodity Flow (MCMCF) problem. Flow of goods on a synchromodal, intermodal or multimodal network can be modelled via a multi-commodity flow problem on a special kind of graph called spacetime network (STN) or space-time graph. This kind of networks consider the schedule of the transportation modes. On this model we build an interactive multi objective analysis method, inspired by Miettinen et al. (2008). As objectives we use the objectives proposed in Ortega Del Vecchyo et al. (2018) to get a robust and flexible planning to be used in the synchromodal environment.

The remainder of this paper is organised as follows. In Section 2 we present the MCMCF problem, and propose and define the new objectives. Then we present the interactive approach and illustrate this by applying it on an example. Finally, in Section 5 we will present the conclusions and give directions for further research.

2 Multi-objective analysis

In this section, we present the MCMCF problem and the Multi Objective Approach. Also we propose and define the new objectives.

2.1. Minimum cost multicommodity flow on space-time graphs

In this section we introduce a modelling framework and notation used, that we need in the remainder of the paper: minimum cost multicommodity flow on space time graphs, based on Crainic (2000). On a graph (G, A) with n nodes and m arcs, where each arc (i, j) has capacity $u_{ij} > 0$, the multicommodity flow problem is a network flow problem with k commodities of d_k demand of flow between different source nodes s_k and sink nodes t_k. The goal here is finding a minimum cost feasible flow.

A formulation of the MCMCF problem is as follows. Let $P(k)$ be the set of all directed simple paths on G from s_k to t_k, C(P) the cost of the path $P \in \cup_k P(k)$, that is, the sum of all the costs of arcs $(i, j) \in P$. Then the MCMCF problem can be formulated as

$$\min \sum_k \sum_{P\in P(k)} C(P) x_P \quad (1)$$

$$\sum_k \sum_{P\in P(k)} x_P\, \delta_{ij}(P) \le u_{ij} \qquad \text{for all } (i,j) \in A \quad (2)$$

$$\sum_{P\in P(k)} x_P = d_k \qquad \text{for all } k \quad (3)$$

$$x_P \ge 0 \qquad \text{for } P \in \cup_k P(k) \quad (4)$$

$$\delta_{ij}(P) = \begin{cases} 1 \text{ if } (i,j) \in P \\ 0 \text{ if } (i,j) \notin P \end{cases} \quad (5)$$

Here, we have one decision variable x_P for each path between an Origin-Destination (OD) pair, for each OD pair.

The MCMCF can be applied to a space-time graph. The idea behind a space-time graph, as its name suggests, is that every node represents a location at a specific time, and arcs represent a change of state. They are meant to show the characteristics of an underlying graph G with node set S as time changes discretely from 1 to T where each of these discrete times is referred to as a time-stamp.

Formally, we say that a graph G is a STN (or space-time graph) if its node set is of the form $S \times \{1,2,...,T\}$ for some $T \in Z^+$ and some set S and every arc $((a, p),(b,q)) \in A(G)$ satisfies $p < q$. We refer to the node (a, p) as location a at time p, and to T as the time horizon of G.

2.2. Objectives

Instead of only minimising costs, now multiple objectives are proposed as defined in Ortega Del Vecchyo et al. (2018). These objectives were constructed using the definitions:

- Robustness is the capacity of a plan to overcome delays in travel times and handling times on terminals and still be carried on as planned.
- Flexibility is the capacity of a plan to adapt to delays in travel times and handling times on terminals when these force the plan not to be able to be carried on anymore.
- Customer satisfaction indicates how satisfied the customer will be if his order arrives a certain time after the due date.

We will give a short derivation of the mathematical definitions of those objective here.

Let $t_0, t_1, t_2 \in Z^+$, $t_0 < t_1 < t_2$. For a given path P on a space-time graph, we say that $e = ((A,t_0), (B,t_1),(B,t_2))$ is an **event** of the path P if the path $((A,t_0),(B,t_1),(B,t_1+1),...,(B,t_2),(C,t_3))$ for some C, B and A is a sub-path of P, and the resource of the trip $((A,t_0),(B,t_1))$ is a different resource than the one of trip $((B,t_2),(C,t_3))$. Also, $e = ((A,t_0),(B,t_1),(B,t_2))$ is an event of P if the path $((A,t_0),(B,t_1), (B,t_1 + 1),...,(B,t_2))$ is a sub-path of P and (B,t_2) is the last node on P. If the event is of the latter form we refer to it as the **last event** of P. We use the short notation $e \in P$ to denote that the event e is an event of the path P. For a path-based multi-commodity flow problem Pr on a space-time graph, we say that e is an event of the problem Pr if it is an event of a path P of an OD pair in Pr. We use the short notation $e \in Pr$ to denote that the event e is an event of the problem Pr. If x_P is the flow variable of a path P, and F is a solution to Pr, the flow on an event $e = ((A,t_0),(B,t_1),(B,t_2))$ is defined as $F_e = \sum_{P \in P(e)} x_P$ where $P(e) = \{P \in \cup_k P(k) | ((A,t_0),(B,t_1)) \in P\}$.

Let F be a solution flow for a path-based multi-commodity flow problem Pr on a space-time graph and the robustness measure $r'(f,t) = e^{-\lambda f/t}$, with $\lambda > 0$ a parameter to be specified depending on the units that represent each timestamp. By defining the robustness measure of an event $e = ((A^e, t_0^e), (B^e, t_1^e), (C^e, t_2^e)$ as $r(e) = r'(F_e, t_2^e - t_1^e)$, we introduce the **geometric mean robustness** of the solution $MR(F)$ as $MR(F) = \left(\prod_{e \in Pr} r(e)\right)^{\frac{1}{|\{e \in Pr\}|}}$.

Definition 1. The geometric mean robustness is minimised by minimising the log of the geometric mean robustness of the solution, calculated by

$$\log MR(F) = \frac{\log \prod_{e \in Pr} e^{-\lambda \frac{F_e}{t_2^e - t_1^e}}}{|\{e \in Pr\}|} = \frac{-\lambda}{|\{e \in Pr\}|} \sum_{e \in Pr} \frac{F_e}{t_2^e - t_1^e}. \tag{6}$$

For a path P on an STN and an event $e = ((A,t_1),(B,t_2),(B,t_3))$ on the path, we define the subpath P_e with respect to e as the subpath of P that contains all the nodes from (B,t_3) onward. Also, for a solution F of a multi-commodity flow problem on a STN G, we denote by $G \backslash F$ the STN G whose arcs' capacity have been lowered according to the flow of F, that is, the capacity of an arc in $G \backslash F$ is the capacity of the arc on G minus the flow passing through that arc on F. Next, for a pair of nodes (A,t_1) and (B,t_2) on a space-time graph G and a positive real number r, we denote by $mincost((A,t_1),(B,t_2),r)_G$ the cost of the optimal solution of the minimum cost flow problem with source node (A,t_1), sink node (B,t_2) and flow r in G. For a path P with flow x_P of a solution F of a multi-commodity flow problem on a STN G and an event $e = ((A,t_1),(B,t_2),(B,t_3))$ on the path, we define the anti-flexibility $\varphi_{G\backslash F}(e, x_P)$ of the event as the least cost that would be incurred if the trip scheduled from A at time t_1 to B at time t_2 would arrive one timestamp after time t_3 to B. That is, $\varphi_{G\backslash F}(e, x_P) = mincost((B,t_3 + 1),(S_P,t_P), x_P)_{G\backslash F} - C(P_e)x_P$. Here, $C(P_e)$ is the cost of the subpath P_e and (S_P,t_P) is the last node on P. Notice the dependency of the min-cost algorithm on the solution flow F as well as on G, that is, the capacity of the arcs on G are lowered corresponding to the flow F. We call the above anti-flexibility because $\varphi_{G\backslash F}(e, x_P)$ decreases as the flexibility of the event increases, according to our definition of flexibility.

Definition 2. For a solution flow F of a path-based multi-commodity flow problem on a space-time graph G and a robustness function r, we define its anti-flexibility

$$\phi_G(F) = \sum_{P\in F, x_P>0} \sum_{e\in P} \varphi_{G\backslash F}(e, x_P)\big(1 - r(e)\big). \tag{7}$$

Definition 3. For a solution flow F of a multi-commodity flow problem Pr on a space-time graph and a family of numbers w(o) ∈ [0,1] such that $\sum_{o\in Pr} w(o) = 1$, we define the customer satisfaction as $(\sum_{o\in Pr} s(o,t_o)w(o))^2$, where to is the delay in number of timestamps of order *o*.

Definition 4. As last objective we define Cost as $\sum_k \sum_{P\in P(k)} C(P)x_P$.

2.3. Multi Objective Approach

First we use a lexicographic method to obtain a Pareto solution. For the lexicographic method we need to rank the objective functions in order of importance. The lexicographic method can be very stiff in some problems, since it doesn't allow for any decrease in value from the top ranked objectives to increase less important objectives. For this reason, we also consider a slight variation of the lexicographic method: when optimising cost, look at the value of number of trucks and constraint the problem with the respect to this number of trucks instead of cost. Notice that, strictly, with this procedure we cannot guarantee that the solution obtained is a Pareto optimal solution, therefore, if a Pareto optimal solution is needed, then one should use the usual lexicographic method. We propose several different orderings for obtaining the (Pareto) solutions, see Table 1.

Table 1: Three lexicographic orders

First	Second	Third
Cost	Cost	Cost
Linear anti-flexibility	Mean Robustness	Customer satisfaction
Customer satisfaction	Customer satisfaction	Linear anti-flexibility
Mean Robustness	Linear anti-flexibility	Mean Robustness

The first order minimises costs and possible unforeseen costs, the second minimises costs and the need to change the plan and the third minimises costs and maximising customer satisfaction. Each of these orderings emphasises on one of the attributes constructed. The solutions provided by the lexicographic methods proposed will serve as a starting point for our interactive method.

Perhaps the most interesting methods of multi-objective optimisation for our case are the interactive methods. On these methods, the user is expected to have input on the algorithm to explore the solutions that are of interest. In Miettinen et al. (2008) the main steps of an interactive method in multi objective analysis are explained in the most general sense. Briefly, these steps are:

1. Provide the Decision Maker (DM) with the range that the different objectives can take, when possible.
2. Provide a starting Pareto optimal solution(s) to the problem.
3. Ask the DMP for preference information.
4. Generate new Pareto optimal solution(s), show them and other possible relevant information to the DM.
5. Stop, or go back to 3.

The purpose of the first two steps is to get the DM to be acquainted with the possibilities and limitations of the problem at hand. The last three steps will also provide further insight to the DM, but are mainly geared towards finding the best Pareto optimal solution with respect to the DM preferences. These kind of methods have some nice benefits. The expertise of the DM is used as input on the method, which should give more satisfactory results from the point of view of the DM. The expert stirs the solution with respect to her or his preferences, and the method provides a solution towards these desired goals. Thus in this method the DM plays a very important role. Next, the decision maker does not need to know in advance the limitations of the problem with respect to the objectives. Rather, she or he learns from the problem at each iteration. Other benefits are that a variety of solutions will be provided, which is a desired feature for our case and that there is no need to have preference for objectives in advance.

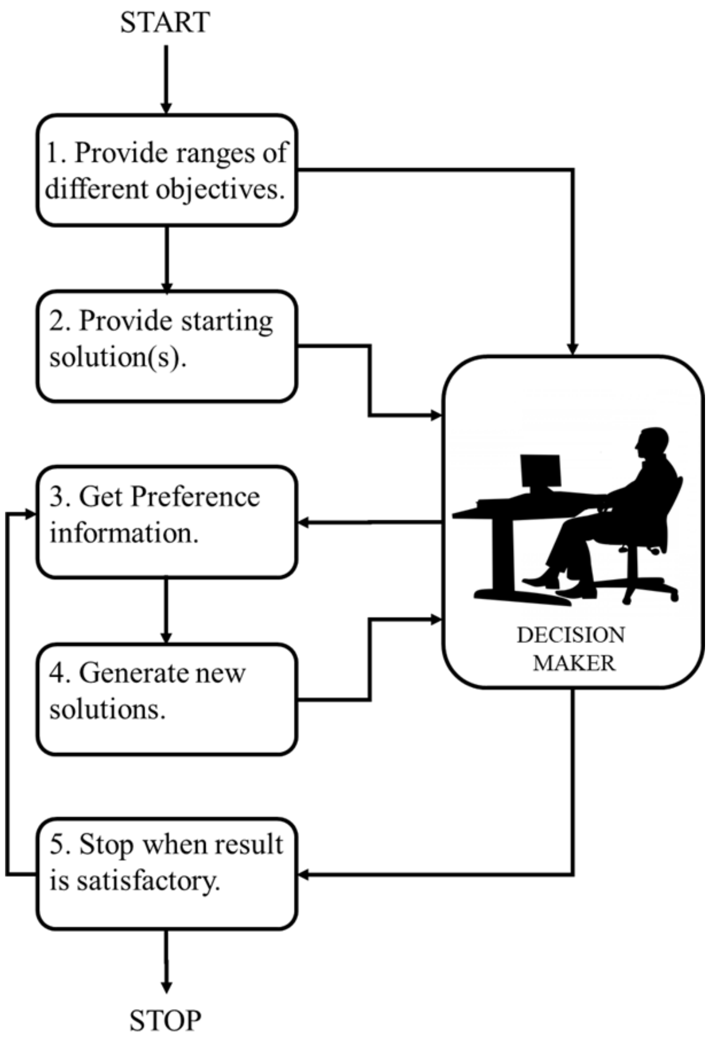

Fig. 1: Proposed approach in flowchart.

3 Proposed Approach

The steps in the planning setting we propose are (see Fig. 1):

1. Provide the decision maker with the range that the different objectives can take, when possible.

2. Provide a starting solution(s) to the problem.

We do not require the starting solution to be a Pareto optimal solution. However, a Pareto optimal solution can provide a valuable insight. The information of these solutions is gathered and kept for further assessment. Additionally, it is useful to build one optimal solution for a scalarisation of each objective (other than cost), that is, the optimal solution of the scalarisation of optimising one objective if cost is allowed a 1% increase with respect to the optimal cost (or, if more margin is given, a greater percentage).

3. Ask the decision maker for preference information.

In this step the influence of the decision maker is crucial. The information available from the solutions of the problem found so far, must be assessed and used to make decisions. This information may include, but is not limited to: (1) The value of the objectives of the solutions obtained so far, for example, the value of the base solution F1 and the influence of achieving this cost in terms of the values of other attributes (obtained from the lexicographic methods); (2) A better assessment of the range of values from the objectives done in step 1, that is, the limitations of the values of attributes; and (3) the approximate time for obtaining a solution, and given the time left for using the method, the number of solution extra we can expect to obtain. From this information the following questions need to be answered:

- What objective to optimise next?
- What range to restrict the rest of the objectives to?
- Is there a minimum capacity needed for owned transport? If so, what percentage?
- Is there a specific arc whose capacity should be updated?
- Is there a path whose value should constrained?

The last question includes whether some trip should not be used, some path must be fixed, some departure time of an arc must be fixed, etc. This characteristic allows the solver to process new information, and therefore, make it more synchromodal. When implemented, instead of building linear programs from scratch, the code modifies the existing linear program to optimise the required objective and satisfy the constraints selected, thus saving computational time.

4. Generate new solutions, show them and other possible relevant information to the decision maker.

A new LP is solved based on the questions obtained from the last step. The information of this solution is gathered and kept for further assessment

5. Stop, or back to 3.

Depending on whether a satisfactory solution has been provided, and on the time available, we either stop the method or reassess.

4 Example

We illustrate the functioning of the interactive method proposed by showing a use case. This method is meant to be used by a decision maker (which in this case is a planner) whose choices will stir the method in a certain direction, thus the method will give different solutions depending on the DM’s preferences. Therefore in this example we consider the presence of a hypothetical planner and conjecture the choices that this fictional DM may make.

Instance. We generate the problem by constructing the space-time graph and the orders to be dispatched on it with the following parameters: 15 terminals (A to O) with infinite capacity, Time Horizon of 200 time units, 400 orders (OD pairs uniformly randomly generated) 16 journeys of transport resources (divided in owned transport and subcontracted transport, other than trucks), and an allowed delay of 10 time units. Handling costs are assumed 0.
Next, we assume the capacity of owned transport within the system 154 and the capacity of a subcontracted transport uniformly distributes between 50 and 55. The number of containers per order can vary between 1 and 30. We assume a Truck price of 40 and the price per container in other transport uniformly distributed between 2 and 4.

To generate the values required for Customer satisfaction, we generate the random values $s(o,t) \in [0,1]$ ensuring that for each o, $s(o,t)$ is decreasing with respect to t. The weights $w(o)$ are uniformly random generated by assigning $w'(o)$ = unif[0,1] to each order and then setting the weight $w(o) = w'(o)/\sum_o w'(o)$.

Interactive method on instance. After the problem has been set, we follow the steps of the interactive method in the synchromodal context. This will be done at each point in time where realisations and new information becomes available and urges the planner to replan.

1. Provide the decision maker with the range that the different objectives can take, when possible. In this case, we have the following possible values: Cost: R+, Anti-flexibility: R, Robustness: [0,1] and Customer satisfaction: [0,1].

2. Provide starting solution(s) to the problem.

We first obtain the base solution F_1 by solving the LP with respect to costs, with no constraint on the other objectives. This results in a solution F_1 with the characteristics shown in Table 2. Suppose the DM chooses to follow the first lexicographic method, then we add the constraint on trucked containers to be less than or equal to 3,420 and optimise linear anti-flexibility. From this we obtain the solution $F_{l,2}$ and, following the lexicographic method, solutions $F_{l,3}$ and $F_{l,4}$ with attribute values as shown in Table 2. These solutions show a very significant decrease in terms of anti-flexibility of 82%, a slight change in mean robustness, and barely any change in terms of customer satisfaction. Notice that neither cost nor anti-flexibility follow a strictly monotonic behaviour with respect to the solution number, despite the fact that this behaviour is expected from a lexicographic method. For the case of cost, this is a consequence of the fact that we are using a slight variation of the lexicographic method where we do not allow trucked containers to increase, instead of cost. For anti-flexibility it is not expected to have any particular monotonic behaviour since it is not constrained directly on the LP. Further analysis on the full transportation plan file corresponding to each solution reveals that despite their similarity in terms of attributes, solution $F_{l,1}$ and $F_{l,4}$ differ on the transport plan of 95 out of 400 orders.

The value of the attributes between solutions is relatively similar because the lexicographic method is quite restrictive, but the solutions provide us the insight of how much are the other attributes subject to change when the cost is (almost) rigid. Also, in this case, as it is often the case on lexicographic methods, the Pareto optimal solution $F_{l,4}$ is a very good proposal in terms of the attributes when compared to the other solutions obtained (that is because all the attributes have been optimised at some stage). This solution will serve as a good reference for the capabilities of the solutions in terms of the attributes.

Table 2: Attribute values of the solutions of the lexicographic method

	F1	Fl,2	Fl,3	Fl,4
Cost	146,387	147,812	147,695	147,653
Mean Robustness	0.8778	0.8831	0.8834	0.8836
Anti-Flexibility	2365.55	442.46	439.82	442.65
Customer Satisfaction	0.8917	0.8907	0.8926	0.8926
Trucked Containers	3420	3420	3420	3420
Linear Anti-flexibility	116.79	20.73	20.73	20.73
Computational Time (seconds)	245	65	85	70

We now calculate the set of solutions corresponding to optimising each objective (that is, scalarisation) allowing 1% increase of cost over the optimal cost. We write F_f , F_r, and F_{cs} for the solution corresponding to flexibility, robustness and customer satisfaction, respectively. The results are summarised in Table 3.

Table 3: Attribute values of solutions

	F_1	F_r	F_f	F_{cs}	F_2	F_3	F_4
Cost	146,387	147,851	147,851	147,844	146,395	146,395	148,352
Mean Robustness	0.8778	0.9056	0.8850	0.8859	0.8761	0.8812	0.8761
Anti-Flexibility	2365.55	626.40	396.84	1498.30	755.53	799.44	801.94
Customer Satisfaction	0.8917	0.9069	0.8937	0.9619	0.9060	0.9060	0.9035
Trucked Containers	3420	3435	3443	3454	3420	3420	3474
Lin. Anti-Flexibility	116.79	36.49	16.53	77.24	39.99	39.99	39.93
Comp. Time (sec.)	245	60	169	729	229.96	2128.02	215.33

From the scalarisation solutions obtained, we can see the extent to which the other attributes can be improved with as little as 1% increase on the cost: customer satisfaction can be improved 0.6 and mean robustness can be increased a bit less than 0.3. In terms of anti-flexibility, there can be a reduction of almost 2000 units. It should be noted that the computational time to derive the solution Fcs is comparatively larger than the other ones.

3. Ask the decision maker for preference information.

At this stage, the decision maker has to assimilate the information she/he has of the problem so far, provided by the previous steps. We conjecture here our fictional DM's train of thought: The values of the attributes of the solutions provide a better idea of the range of the attributes: customer satisfaction is quite cost-effective to improve. Also, from $F_{l,2}$ and F_f we see that anti-flexibility can be reduced substantially for little cost. Additionally the DM knows that for this particular problem any plan with a customer satisfaction value over 0.9 is acceptable. Therefore the DM chooses the next solution to be the solution F_2 of the scalarisation of optimising cost with a constraint on linear anti-flexibility of 40 and a customer satisfaction of 0.9.

4. Generate new solutions, show them and other possible relevant information to the decision maker.

Solution F_2 (see Table 3) has just an increase of 8 in terms of cost, and it provides a very substantial decrease on anti-flexibility, as well as an increase in customer satisfaction.

5. Stop, or back to 3.

The solution seems satisfactory, but the DM decides to try to improve the robustness of the solution without compromising the other attributes, resulting in a new step 3':

3'. The DM decides to optimise with respect to robustness, with cost, linear anti-flexibility and customer satisfaction to be at as good as the values in F_2 (similar to a lexicographic method).

4'. We obtain a solution F_3 (see Table 3). Notice that the computational time to obtain F_3 is quite long, therefore, depending on the time available, the DM may have stopped the simulation, and picked a solution from the solutions obtained so far (probably F_2). This of course depends on the importance the DM gives to improving slightly the robustness of the solution in this circumstances.

5’. Suppose the DM choose not to finish the simulation to obtain F_3 and reports F_2 as her/his solution of choice. The DM reviews the solution obtained and is informed that F_2 uses a specific trip that has been cancelled, which is represented by the arc ((‘K’,35),(‘L’,44)) on the space-time network used for the problem. She/he is also informed that another trip from another transport used in F_2 will not be departing at the time the plan F_2 uses it, which is represented by arc ((‘C’,48),(‘I’,54)). Additionally, a particular order has been specified to be served exclusively via truck, namely, order 2. The DM is therefore forced to go back to 3 again, noted by 3’’:

3’’. With these new constraints, the DM has to make a choice depending on the time available: Either build a solution F_4 using constraints like the ones used to obtain the best solution so far, namely, F_2, or restart from step 1 considering the problem with this new added constraints as a new problem. Assuming a decision must be taken in a short time, the DM decides for the former

4’’. The new constraints are added to the LP. We then optimize cost constraining linear anti-flexibility to 40 and a customer satisfaction of .9 and obtain the solution F_4.

5’’. The DM is satisfied with the attribute values and proposes F_4 as a solution.

5 Conclusions and future work

We developed an interactive multi-objective optimisation method, which is meant to be used as a decision support tool for planners. This tool provides the user the possibility to explore solutions as she/he seems fit, and provides a range of different planning solutions for the planner to choose from, which are both properties sought for in a decision support tool.

The method above proposes a hypothetical scenario where a planner uses this tool for the purpose of making a plan. However, the tool itself is an optimizing method and it could be used for other purposes, for example, given a particular problem, it can quantify the impact that certain attributes have on cost, such as the delayed delivery, or the minimum capacity on barges. This could illustrate how certain behaviours on the network are affecting the cost-performance of the network, or how some advantages are not being exploited.

In order to understand the tool, the user needs familiarisation with the concepts used, such as space-time network, optimisation, and a fair notion of the mathematics involved. Since the goal of this tool is to illustrate the benefits that can come from planners using multi-objective optimisation, it is very important to keep things simple. Therefore the command inputs proposed in this method attempt to be used and understood (as much as possible) by a non-technical user. On the other hand, when compared to other interactive solution approaches in the literature, this method requires less input from the DM, and also less technical expertise. As future work, once the value of such a tool has been acknowledged by the planners, and the planners are committed to the interactive use of the tool, the complexity and usage of the tool can be increased. If more advanced interactive methods are developed, there should always be sensitivity into the context, use and level of involvement of the DM.

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