

Appendix

A. Algorithm for the overall process of decision-making

Given the definition of an IDN and cost terms presented in subsection 4.2, we present in Algorithm 1 the solution process for a given state s_θ .

Algorithm 1

Require: $\mu_v^{v'} \forall (v, v') \in \{(v, v') | v \in N, v' \in N\}; s_\theta$

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1: for  $k \in K_\theta$  do
2:   Enumerate the set  $D_\theta^k$  of all nodes that meet the IDN criteria in Definition 1
3: end for
4: for  $k \in K_\theta$  do
5:   for  $(v', t') \in D_\theta^k$  do
6:     Calculate the approximated costs  $\Omega_{(v', t')}^{k\theta}$ 
7:   end for
8: end for
9: Formulate the MILP minimize (21) subject to constraints (9) - (16)
10: Solve the MILP and retrieve the decisions on  $\bar{\delta}_\theta = (\bar{x}^\theta, \bar{m}^\theta)$ 
11: return  $\bar{\delta}_\theta$ 

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The state contains all relevant information, namely the time point at which the decision epoch starts as well as the known commodities. First it must be searched for all IDN set (line 1 - 3) of every commodity. This searches for all nodes that match the criteria from definition 1. If an IDN set D_θ^k has been determined for all commodities, the approximation of the costs $\Omega_{(v', t')}^{k\theta}$ can be made for each IDN, which is required for the objective function (line 4 - 8). For this all steps, described in Subsection 4.2, must be completed. After the approximation of the costs is done, the MILP is set up using these cost approximations for the nodes in the IDN set (line 9) and solved (line 10). Finally, the individual decisions about route plans of the commodity and used transport services are extracted and returned as decision $\bar{\delta}_\theta$ (line 11).

B. On the size and runtime of MIPs

In this section, we take a closer look at MIPs, their runtimes and performance gaps. We will examine four relevant factors: the average number of linear constraints in every decision epoch, the average number of decision variables in every decision epoch, the overall runtime and the average performance gaps of the MIPs in every decision epoch. However, commodities were not routed in every experiment until the end of the planning horizon at $T = 25$. For this reason, all average values in the following tables (3, 4, 5) were calculated only using decision epochs in which a commodity was routed. The Go-as-fast-as-possible and Wait-as-long-as-possible methods are excluded from this analysis, as they could be solved without a MIP and the runtime was less than one second in all instances.

First, we take a look at the overall runtime of the instances. Table 2 shows the average time each method took to solve the instances for different delivery and size settings. While Slack IDN and Myopic have relatively short runtimes,

delivery setting	size setting	Slack IDN (in s)	Myopic (in s)	Direct Lookahead (in s)	CFA (in s)
fast	small	266	2330	85,332	31,803
fast	medium	295	2471	89,269	33,904
fast	large	298	3254	92,492	39,163
fast	extra	294	3322	91,870	43,688
moderate	small	305	4726	114,902	57,062
slow	small	380	7270	121,374	68,837

Table 2 Runtime comparison for different delivery and size settings.

delivery setting	size setting	Slack IDN	Myopic	Direct Lookahead	CFA
fast	small	9,286	14,748	43,315	12,689
fast	medium	9,286	14,735	43,118	12,685
fast	large	9,286	14,713	42,901	12,702
fast	extra	9,286	14,713	43,068	12,716
moderate	small	9,369	18,573	54,304	15,700
slow	small	9,369	21,859	66,462	18,108

Table 3 Comparison of the average number of linear constraints in a decision epoch for different delivery and size settings.

delivery setting	size setting	Slack IDN	Myopic	Direct Lookahead	CFA
fast	small	43,986	90,203	308,182	73,075
fast	medium	43,986	90,026	306,947	73,201
fast	large	43,986	90,010	304,563	73,109
fast	extra	43,986	89,881	305,411	73,117
moderate	small	43,980	123,186	407,267	97,431
slow	small	43,980	152,733	516,788	117,978

Table 4 Comparison of the average number of decision variables in a decision epoch for different delivery and size settings.

the runtimes for Direct Lookahead and CFA are significantly longer. However, there are also significant differences between these two methods. For example, the average runtime of the CFA across all instances is 45,743 seconds, while the average of Direct Lookahead is 99,207 seconds. This means that Direct Lookahead takes, on average, more than twice as long to solve a problem instance.

Tables 3 and 4 illustrate the size of the MIP. They show the average number of linear constraints and decision variables in each decision epoch for various delivery and size settings when using different methods. It is noticeable how much larger the average MIP is in the decision epochs when using Direct Lookahead. This is, of course, due to the fact that a period twice as long is considered. It is also important to note the impact of extending the delivery window: The more time the commodities have, the larger the MIPs generally become, as they are shipped over a longer period. The only exception is Slack IDN, but this can be explained by how the method works. Since the IDN with the highest slack is always selected, routing decisions are generally independent of the due date of the commodities.

Finally, we examine the average performance gaps of the MIPs for the various methods. These are specified for the different settings in Table 5. It can be seen that for all methods except Direct Lookahead, the gaps are less than 2 and in most cases even 0. The large gaps in Direct Lookahead are likely due to the fact that larger problems are being considered, which cannot be fully solved within the two-hour time window we specified.

delivery setting	size setting	Slack IDN (%)	Myopic (%)	Direct Lookahead (%)	CFA (%)
fast	small	0.00	0.00	4.50	0.23
fast	medium	0.00	0.00	4.83	0.32
fast	large	0.00	0.00	5.16	0.30
fast	extra	0.00	0.00	5.06	0.51
moderate	small	0.00	0.00	9.16	0.92
slow	small	0.00	0.00	11.55	1.55

Table 5 Comparison of the average MIP Gaps in a decision epoch for different delivery and size settings.

delivery setting	size setting	CFA (%)	CFA-A* (%)
fast	small	100	103.175
fast	medium	100	102.746
fast	large	100	102.623
fast	extra	100	102.862
moderate	small	100	103.554
slow	small	100	104.032

Table 6 Relative costs comparison of CFA and CFA-A* under various delivery and size settings.

delivery setting	size setting	CFA (in s)	CFA-A* (in s)
fast	small	31,803	20,886
fast	medium	33,904	22,135
fast	large	39,163	27,221
fast	extra	43,688	33,763
moderate	small	57,062	33,686
slow	small	68,837	50,032

Table 7 Runtime comparison of CFA and CFA-A* under various delivery and size settings.

C. On the reduction of decision space

In the following, we will explore a way to narrow down the decision space in order to reduce the runtime of the problems without significantly compromising the quality of the solutions. Here, as in Appendix B, the experiments were conducted with $T = 25$; however, for the calculation of the averages, only decision epochs in which commodities were routed (i.e., in which an MIP was generated) were included (see table 8, 9 and 10). Next, we examine the results:

Table 6 compares the costs of the CFA-A* relative to the CFA under various delivery and size settings. On average, the CFA-A* generates 3.166% higher costs. It is notable that the cost difference increases with a slower delivery setting. Although the increase is only small, the reason for this could be that, when given more time, commodities are routed via longer detours, as shown in Table 6. Since not all detours are possible due to the detour restriction, the result deteriorates.

The runtimes of the two methods under various delivery and size settings are shown in Table 7. On average, solving the instances using the CFA takes 45,743 seconds, while when using CFA-A* solving takes only 31,287 seconds. The runtime is therefore about 31.6% shorter. These savings are most likely attributable to the smaller number of linear constraints and decision variables in the individual MIPs at the decision epochs. On average, the MIPs at the decision epochs when using CFA-A* have 11,228 linear constraints, while the MIPs when using CFA have 14,100 constraints. The situation is similar when considering the average number of decision variables at the decision epochs. When using CFA-A*, the MIPs have an average of 44,026 decision variables, and when using CFA, 84,652. Tables 8 and 9 show

delivery setting	size setting	CFA	CFA-A*
fast	small	12,689	10,201
fast	medium	12,685	10,215
fast	large	12,702	10,261
fast	extra	12,716	10,270
moderate	small	15,700	12,395
slow	small	18,108	14,027

Table 8 Comparison of the average number of linear constraints in every decision epoch when using CFA and CFA-A* under various delivery and size settings.

delivery setting	size setting	CFA	CFA-A*
fast	small	73,075	39,465
fast	medium	73,201	39,566
fast	large	73,109	39,769
fast	extra	73,117	39,814
moderate	small	97,431	49,082
slow	small	117,978	117,978

Table 9 Comparison of the average number of decision variables in every decision epoch when using CFA and CFA-A* under various delivery and size settings.

delivery setting	size setting	CFA (%)	CFA-A* (%)
fast	small	0.23	0.09
fast	medium	0.32	0.12
fast	large	0.30	0.16
fast	extra	0.51	0.22
moderate	small	0.92	0.22
slow	small	1.55	0.39

Table 10 Comparison of the average MIP gap in every decision epoch when using CFA and CFA-A* under various delivery and size settings.

the average number of linear constraints and decision variables in the decision epochs for various delivery and size settings when using CFA and CFA-A*.

Finally, Table 10 shows the MIP gaps for the various delivery and size settings. While using CFA-A* the MIP gap is less than 0.4% across all settings, when using CFA the MIP gap rises to as high as 1.55%. This is likely also related to the size of the MIPs, as described earlier. Overall, the CFA-A* offers a way to significantly reduce the runtimes, but this comes at the cost of a slight deterioration in cost performance even though the MIP gaps are smaller.

D. Analyzing the scalability by varying the number of commodities

All of our experiments were conducted using different settings for λ . Here, λ represents the average number of commodities shipped per day (for more detail see chapter 5.1). In the following, we examine how the CFA and its benchmark methods perform when more or fewer new commodities appear each day. It should be noted that the methods Go-as-fast-as-possible and Wait-as-long-as-possible have been abbreviated as Gafap and Walap.

Table 11 shows the relative costs of the various methods compared to the CFA when considering different values for λ . Our CFA performs best in every scenario and also outperforms the Direct Lookahead. Particularly with the methods Go-as-fast-as-possible, Wait-as-long-as-possible, Slack IDN and Myopic, performance declines as the number

λ	Gafap	Walap	Slack IDN	Myopic	Direct Lookahead	CFA	CFA-A*
20	2.080	2.045	1.977	1.529	1.054	1	1.021
40	2.429	2.391	2.247	1.572	1.045	1	1.034
60	2.728	2.690	2.480	1.605	1.047	1	1.039

Table 11 Relative costs comparison of different values for λ .

of commodities per day increases, compared to the CFA. This also applies to CFA-A*. The only exception is Direct Lookahead, where performance is worst for the smallest λ of 20.

E. Proof of Proposition 1

Proof of Proposition 1 As the values $\bar{x}_{(v,t),(v',t')}^{k\theta}$ satisfy constraints (1), (2), and (3) they define a sequence of nodes in N_θ^* for commodity k that begins at (o_θ^k, a_θ^k) and terminates at (d^k, e^k) . Namely, we have the sequence $((u_1, t_1), \dots, (u_n, t_n))$ with $u_1 = o_\theta^k, t_1 = a_\theta^k$ and $u_n = d^k, t_n = e^k$ and $(u_j, t_j) \in N_\theta^*, j = 1, \dots, n$. Let (u_{j*}, t_{j*}) be such that t_{j*} is the smallest of $t_1, \dots, t_n$ such that $t_{j*} \geq t_\theta + l$. Because $e^k \geq t_\theta + l$ such a t_{j*} must exist. We will next show that (u_{j*}, t_{j*}) satisfies the conditions of Definition 1.

We first observe that the sequence of locations, $(u_1, \dots, u_{j*})$ implies that the path $p_{o_\theta^k}^{u_{j*}}$ exists and thus (u_{j*}, t_{j*}) satisfies condition 1. Second, the choice of t_{j*} ensures that both conditions 2 and 3 are satisfied. Finally, as $t_n = e^k$ we must have $\Delta_{u_{j*}}^{d^k} = \sum_{j=j*}^{n-1} \tau_{jj+1} \leq e^k - t_{j*}$. Or, in words, the length in time points of the path from u_{j*} to d^k is no greater than $e^k - t_{j*}$. Alternately, we have that $t_{j*} + \Delta_{u_{j*}}^{d^k} \leq e^k$. As we must have $\mu_{u_{j*}}^{d^k} \leq \Delta_{u_{j*}}^{d^k}$ by definition, condition 4 is satisfied.

F. Proof of Proposition 2

Proof of Proposition 2. We first show that $proj_{\theta, \theta+1}(P_\theta) \in R_\theta$. Let $(\bar{x}^\theta, \bar{m}^\theta)$ be an element of $proj_{\theta, \theta+1}(P_\theta)$. By definition, for each commodity $k \in K_\theta$ such that $e^k \geq t_\theta + l$ there are values $\bar{x}_{(v,t),(v',t')}^{k\theta}$ for $((v,t), (v',t')) \in E_\theta^* \setminus E_{\theta, \theta+1}^*$ that enable the construction of a single sequence of nodes for commodity k from (o_θ^k, a_θ^k) to (d^k, e^k) . As in the proof of Proposition 1, an IDN (v'_k, t'_k) can be identified from this sequence. Let $\bar{z}_{(v',t')}^{k\theta} = 1, \bar{z}_{(u,t)}^{k\theta} = 0 \quad \forall (u,t) \in D_\theta^k$ such that $(u,t) \neq (v',t')$. As such, one can see that $(\bar{x}, \bar{m}, \bar{z})$ satisfy constraints (11) - (16) and thus $(\bar{x}^\theta, \bar{m}^\theta, \bar{z}^\theta) \in Q_\theta$ and $(\bar{x}^\theta, \bar{m}^\theta) \in R_\theta$.

We next show that $R_\theta \in proj_{\theta, \theta+1}(P_\theta)$. Consider an element $(\bar{x}^\theta, \bar{m}^\theta) \in R_\theta$ and a corresponding set of values $\bar{z}^\theta$ such that $(\bar{x}^\theta, \bar{m}^\theta, \bar{z}^\theta) \in Q_\theta$. For each commodity $k \in K_\theta$ such that $e^k \geq t_\theta + l$, we consider the IDN $(v', t') \in D_\theta^k$ such that $\bar{z}_{(v',t')}^{k\theta} = 1$. By condition 4 of Definition 1 one can construct a path consisting of arcs from $E_\theta^* \setminus E_{\theta, \theta+1}^*$ such that the first arc departs from (v', t') and the last arc arrives at (d^k, e^k) . Such a sequence of arcs can be used to construct values $\bar{x}_{(v,t),(v',t')}^{k\theta}$ such that $(\bar{x}, \bar{x}, \bar{m}) \in P_\theta$ and thus $(\bar{x}, \bar{m}) \in proj_{\theta, \theta+1}(P_\theta)$.