

Contingent versus Deterministic Plans in Multi-Modal Journey Planning

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Abstract

Deterministic planning is the de facto standard in deployed multi-modal journey planning systems. However, in reality, transportation networks feature many types of uncertainty, including variations of the arrival and the departure times of public transport vehicles. Under uncertainty, deterministic plans could result in missed connections, leading to an arrival time much worse than originally planned.

We contribute an empirical study using transportation network data from three European cities. We show that, in the presence of uncertainty, contingent plans can often provide significant savings in terms of travel time. We view our results as important because they advocate adopting uncertainty-aware multi-modal journey plans, shifting from the current practice based on using deterministic planning.

Introduction

Multi-modal journeys in a city allow to combine, as part of the same trip, multiple transportation modes, such as buses, trams, subways and trains. Multi-modal journey planning has attracted a substantial interest in recent years. Increasing levels of congestion and pollution justify in part the need for adopting, on a larger scale, multi-modal transport.

In deployed multi-modal journey planning systems, the standard practice is to compute journey plans under deterministic assumptions. However, in reality, transportation networks feature many types of uncertainty, such as variations of the arrival and the departure times of scheduled public transport. These can cause undesirable failures in a journey, such as missed connections, which can further negatively impact the total travel time.

Stochastic multi-modal planning has recently been introduced as a way of hedging the risks associated with missed connections (Botea, Nikolova, and Berlingerio 2013; Nonner 2012; Nonner and Laumanns 2014). Unlike deterministic plans, that typically are totally ordered sequential plans, stochastic plans are in fact policies that can include multiple options in the same state. Even if a connection is missed out, alternative options included in the policy may allow to continue the trip and arrive at the destination within a reasonable time. For example, Botea, Nikolova, and Berlingerio (2013) use contingent plans (Peot and Smith 1992)

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where all options (branches) in a given state are prioritized, and each branch has a given probability of being followed at the execution time.

In principle, potential advantages of a contingent plan (policy) over a deterministic plan are not difficult to point out, as discussed in the next section. An important question is whether contingent plans would make any significant difference in a real transportation network.

We contribute an experimental study with data from the transportation networks of three European cities. Our results demonstrate that contingent plans can significantly improve the arrival time in transportation networks that feature uncertainty. They also give more accurate apriori indications of the actual arrival time. The main findings are consistent across the cities, despite differences in size and transport modes available. Our study shows a limitation in the standard, de facto practice of using deterministic planning. It provides evidence that supports adopting uncertainty-aware multi-modal journey planning in practice.

Contingent vs Sequential Journey Plans

In this section we illustrate potential differences between contingent and sequential journey plans in the presence of uncertainty. For simplicity, we consider just the arrival time as the plan quality metric, and discuss differences in terms of worst-case and best-case arrival times.

Aspects covered in this section are not new on their own. However, it is important to articulate potential differences upfront, to set the background to our experimental study.

Consider the example illustrated in Figure 1, where a user wants to travel from *A* to *B*. As shown in Table 1, there are three ways to complete the journey. Each of these can be seen as a separate sequential plan. In plan 1, it is uncertain whether the connection at stop *C* will succeed, due to the variations in the arrival and departure times of routes 38 and 40, illustrated in Figure 1.

The best policy is a combination of the sequential plans 1 and 3, as follows. Take bus 38 from *A* to *C*. If it's possible to catch bus 40 that departs at 11:21, take it from *C* to *E*, and then walk to *B*. Otherwise, walk to stop *D*, take bus 90 at 11:30, get off at stop *F*, and walk to *B*. The arrival time is ~12:10pm (best case) or ~12:20pm (worst case).

This policy is an example of a contingent plan (Peot and Smith 1992). A contingent plan can be viewed as a tree of

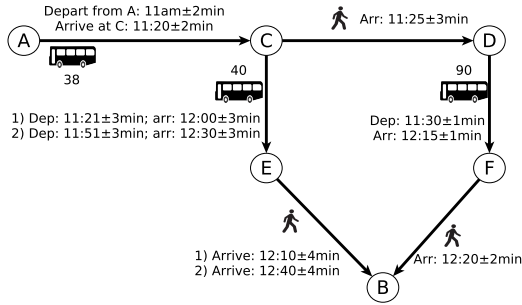


Figure 1: A toy example with bus links and walking links.

Seq. plan	Steps	Remarks
1	11:00 – Bus 38 to C 11:21 – Bus 40 to E 12pm – Walk to B	Uncertain connection in C Arrive at around 12:10
2	11:00 – Bus 38 to C 11:51 – Bus 40 to E 12:30 – Walk to B	Arrive at around 12:40
3	11:00 – Bus 38 to C 11:20 – Walk to D 11:30 – Bus 90 to F 12:15 – Walk to B	Arrive at around 12:20

Table 1: Sequential plans in the example.

pathways from the origin to the destination. In this work, a contingent plan includes both priorities and probabilities associated with the options available in a state. In the example, the contingent plan contains a branching point at location C . The option of taking bus 40 that departs at around 11:21am has the highest priority. Walking to stop D is the backup, lower-priority option. The probability p of following the first option can be computed from the distributions of two random variables (Botea, Nikolova, and Berlingerio 2013). One variable models the arrival time of the traveller at stop C , which in our example coincides with the arrival time of bus 38. The other variable is the departure time of bus 40. The probability of taking the backup option is $1 - p$.

As sequential plans are restricted to one unique trajectory each, no sequential plan is capable of matching the performance of the best policy in the running example. For instance, while plan 3 matches the worst-case arrival of the policy, it is weaker than the policy in terms of the best case arrival time. The sequential plan 2 is weaker in terms of both worst-case and best-case arrival times.

Plan 1 is weaker in terms of the worst-case arrival. But what is the worst-case arrival time of the sequential plan 1 anyways? To answer this question, we note that, in the case of a missed connection, sequential plans have the implicit backup option of waiting for the next trip on the same route. Hence, in the sequential plan 1, in the worst case, the user will wait for the next trip on route 40, which arrives at around 11:51. As this implicit backup option of plan 1 is essentially equivalent to plan 2, we conclude that the worst-

case arrival time for plan 1 is about 12:40pm.

More generally, a sequential plan can be optimal if it is both *safe* (i.e., all actions in the sequence will be applicable with probability 1) and *fast* (i.e., the arrival time is optimal). On the other hand, as shown in the example, there can exist states where one option is good (i.e., providing a good arrival time) but uncertain, whereas another option is safe but slower. These are cases where sequential plans lose their ability to implement an optimal policy, and where contingent plans can make a difference, as illustrated in our example.

The Tools

In our study, we use Docit (Botea et al. 2014; Nonner, Botea, and Laumanns 2014), an existing research prototype. Docit provides functions such as journey plan computation, plan execution monitoring, and replanning. We are not aware of any other multi-modal journey advisor that reasons about uncertainty. The Docit components that are the most relevant to our study are the Dija multi-modal journey planner (Botea, Nikolova, and Berlingerio 2013), and a simulator for plan execution.

Dija computes contingent plans with AO* (Nilsson 1968; 1980) search. The cost metric is a linear combination between the travel time and the number of legs in a journey. It optimizes plans based on a combination of two criteria. The main criterion is the worst-case cost (i.e., the largest cost along all possible pathways in a contingent plan). This is a key criterion in those cases where meeting a deadline (e.g., arrive in time for an important meeting) is important. Ties are broken by preferring plans with a better expected cost. The expected cost is the weighted sum of costs across all pathways in a contingent plan, each weight being the probability of taking that particular pathway (Botea, Nikolova, and Berlingerio 2013).

The simulator takes as input a *network snapshot*¹ n , a plan p , a state s in the plan, and a stochastic time t (a probability distribution). It simulates the rest of the plan, starting from state s and from time t , given the network snapshot n . The simulation is a recursive procedure that returns both the worst-case and the expected arrival time. The recursions simulate forward the travel along each pathway, and propagate the arrival times from the leaves all the way up.

For instance, when simulating the worst-case arrival time, for every journey leg (i.e., transition in the plan) considered in the simulation, the simulator takes the quickest way of completing that leg that is *certain* to be applicable. In other words, for a leg involving a public transport vehicle (e.g., bus), the simulator takes the earliest trip that is certain to catch. As mentioned previously, the probability of catching a trip in a state s' depends on the departure time of the bus at state s' , which is taken from the network snapshot, and the arrival time of the user at state s' . This arrival time is t when $s' = s$, and it is provided by the simulation of the previous step in subsequent states s' . In the example, when simulat-

¹The snapshot is a knowledge base with all information available about a given transportation network. It can include stops, routes, trips with arrival and departure times provided for each stop along the route, bike stations, car parking lots, and road map data.

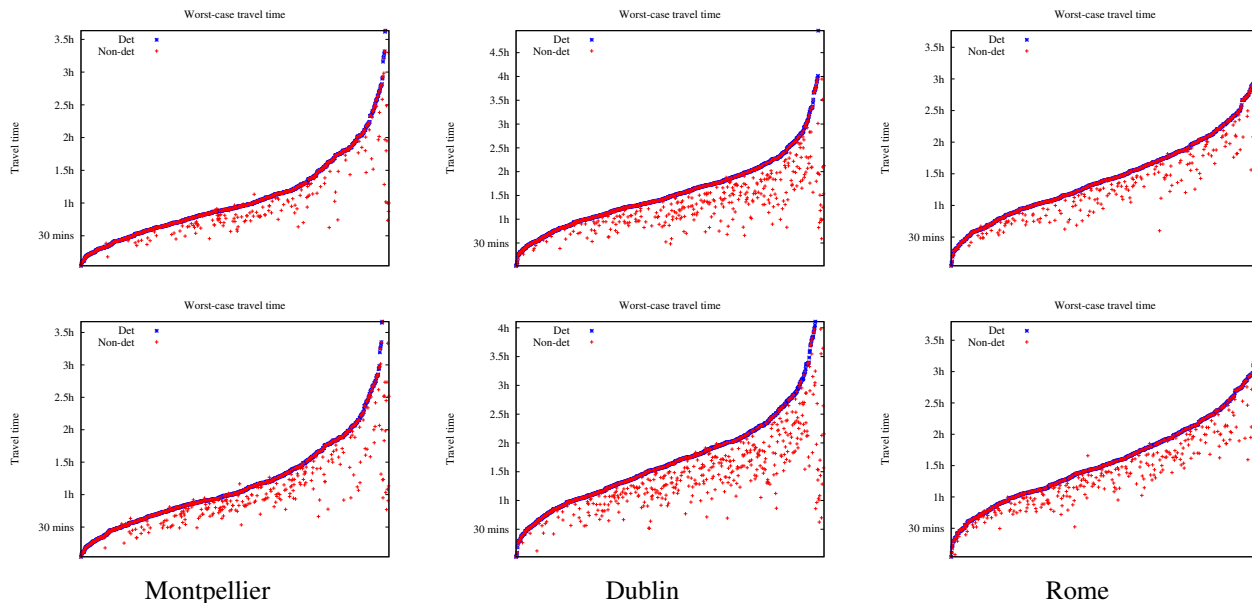


Figure 2: Top: $\sigma^2 = 1600$; bottom: $\sigma^2 = 6400$. Sequential plans (“Det”) vs contingent plans (“Non-det”). Instances ordered increasingly on the worst-case arrival time of sequential plans.

ing the leg from C to E starting at 11:20am, the earliest trip safe to catch is the one departing from C at around 12:00. This is why the worst-case arrival time for sequential plan 1 is actually 12:40, 30 minutes later than indicated by the deterministic plan.

In the bottom-up propagation of arrival times, the worst-case arrival time associated with a non-leaf state is set to the best of the worst-case arrival times of its children.

In Docit, the main purpose of the simulator is to decide whether a given journey plan is still valid when new information about the transportation network is loaded (e.g., when real time updates on arrival and departure times are available). This allows, for example, to detect a subset of active journeys that get invalidated by an event, such as a disruption on a tram line (Botea et al. 2014). Replanning can be performed only for the subset of the invalidated plans.

In this work, we use the simulator to evaluate differences between plans computed under deterministic assumptions (i.e., no uncertainty in the network snapshot), and plans computed by taking uncertainty into account. The results are discussed in the next section.

Experiments

We used data from three European cities, Montpellier, Dublin, and Rome. Our Dublin Bus data contain 4,739 stops, 120 routes, and 7,308 trips per day. The road network has 301,638 nodes and 319,846 segments. In Montpellier, scheduled public transport includes buses and trams. There are 1,297 stops, 36 routes and 3,988 trips per day in our data. The road network has 152,949 nodes and 161,768 links. In Rome, buses, trams, subways and light trains sum up to 391 routes. There are 39,422 trips per day, and 8,896 stops. The road map contains 522,529 nodes and 566,400 segments.

City	DP	ASM	ASP	DP	ASM	ASP
	$\sigma^2 = 1600$			$\sigma^2 = 6400$		
Dub	30.48%	28.95	25.77%	41.75%	29.04	24.23%
Rom	23.85%	16.71	18.08%	32.70%	18.10	18.35%
Mon	14.56%	17.05	22.43%	23.75%	18.67	22.93%

Table 2: Contingent vs deterministic plans: key statistics with worst-case travel time. DP = percentage of cases when differences occur. ASM = average savings per trip, in minutes, when differences occur. ASP = average savings per trip, as a percentage of the trip time, when differences occur.

The original data is deterministic. This was extended with a stochastic noise assigned to the original deterministic arrival and departure times. More specifically, for each city we use three distinct network snapshots, one deterministic (i.e., the original snapshot), and two with different levels of stochastic noise. The noise follows a Normal distribution, truncated to a confidence interval of 99.7%. One snapshot has the variance set to $\sigma^2 = 1600$ seconds, equal roughly to ± 2 minutes around the original deterministic arrival or departure times. In the other snapshot, we set $\sigma^2 = 6400$ (equal roughly to ± 4 minutes).

We generated 3,000 journey plan requests (instances) for each city, with 1,000 for each of the following departure times: 8am, 11am and 6pm. The origins and the destinations are picked at random. Trips are constrained to no more than 20 minutes of walking, and at most 5 legs (segments) per trip. For space reasons, we restrict our attention to 11am data, a representative subset of the results.

To obtain a deterministic, sequential plan, we have run Dija (Botea, Nikolova, and Berlingerio 2013) with a de-

terministic network snapshot. Uncertainty-aware plans are computed with Dija using a non-deterministic snapshot. Both kinds of plans are simulated in a snapshot with uncertainty, and both the worst-case arrival time and the expected arrival time are measured.

Worst-case arrival time. Figure 2 compares deterministic and uncertainty-aware plans, in terms of simulated worst-case arrival time, for Montpellier, Dublin and Rome. The “main curve” shows the deterministic-plan data.

Depending on how “det” and “non-det” values compare, we distinguish three behaviours in this figure. First off, in a majority of cases, ranging from 58.25% in Dublin, $\sigma^2 = 6400$ to 85.44% in Montpellier, $\sigma^2 = 1600$, “non-det” points fall on the “main curve”, indicating instances where both simulated times coincide. Secondly, in most remaining cases, “non-det” points fall underneath the main curve, corresponding to cases where contingent plans have a better simulated time. Table 2, discussed later, shows exact percentages and other key statistics corresponding to this behaviour. Thirdly, in just a few cases, deterministic plans have a better arrival time. Part of the explanation is that the Dija planner optimizes plans on a linear combination of the number of journey legs (segments) and the arrival time. In a few cases, the optimal contingent plan has a longer arrival time, and fewer legs than the corresponding deterministic plan.

We conclude from Figure 2 that uncertainty-aware plans can often help arrive at the destination earlier.

Table 2 shows key statistics of the comparison. Header DP shows the percentage of “Non-det” dots not placed on the main curve in Figure 2. As expected, increasing the level of uncertainty increases the DP value. Remarkably, ASM and ASP remain stable when σ^2 varies.

Furthermore, it appears that DP, ASM and ASP depend on the “density” of the trips in a city (number of trips relative to the size of the network). For instance, in the data we used, Dublin has a smaller number of trips than Rome, which increases the DP, the ASM and the ASP values in the former city. A similar tendency is observed when varying the number of trips in a given city. In a different experiment, we have used a larger number of trips, obtained by combining trips from different days and, in the case of Dublin, including a few tram and train lines in addition to the existing bus routes. More trips in use reduce DP, ASM and ASP. For instance, increasing the number of trips per day in Dublin from 7,308 to 21,056 reduces DP to 32.45%, ASM to 18.18 minutes and ASP to 15.71% ($\sigma^2 = 6400$). In Montpellier, an increase from 3,988 to 5,985 trips per day results in DP = 16%, ASM = 13.02, ASP = 16.36% ($\sigma^2 = 6400$).

Expected arrival time. On this metric, differences between contingent and deterministic plans are smaller, and they go in both directions. This is consistent with the planner’s optimization strategy: the worst-case cost is the main criterion, and the expected cost is used for tie-breaking.

For example, in the case of Dublin, $\sigma^2 = 1600$, 11.52% cases favour contingent plans. When this happens, the average savings in terms of expected arrival time are 12.32 minutes, or 13.08% of the expected trip duration. 7.76% cases are in favour of deterministic plans, with average time savings per trip equal to 10.95 mins (13.29%). For $\sigma^2 = 6400$,

16.12% cases are in favour of contingent plans, and 11.19% cases favour deterministic plans. Average savings per trip are similar to the previous case. In Rome, $\sigma^2 = 1600$, 7.03% cases show an advantage for contingent plans, and 7.49% cases favour deterministic plans. When $\sigma^2 = 6400$, the numbers change to 12.63% and 8.53%. In Montpellier, $\sigma^2 = 1600$, 3.35% cases favour contingent plans and 4.51% cases favour deterministic plans. Setting the variance σ^2 to 6400 changes these values to 6.16% and 5.51% respectively.

Dynamic deterministic replanning (DDR). We have implemented a strategy that performs, in every state, a deterministic replanning, but simulates the first leg of each plan under a snapshot with uncertainty. We have measured the simulated worst-case arrival time. DDR is better than deterministic planning, but not as good as contingent planning. For example, when comparing DDR to contingent plans, the percentage of cases favourable to contingent plans varies from 4.80% (Montpellier, $\sigma^2 = 1600$) to 19.24% (Dublin, $\sigma^2 = 6400$). The percentage of cases favourable to DDR is smaller, varying between 0.20% and 2.33%.

Search time. As expected, the search time increases with σ^2 . Interestingly, a reduced trip frequency (as in our Dublin data) makes a search more difficult. We attribute this to the following effect on the accuracy of the admissible heuristic estimation for the travel time. Less frequent trips result in more waiting in a trip. At the same time, the travel time admissible heuristic (Botea, Nikolova, and Berlingerio 2013) ignores any waiting time. Thus, the more waiting in a trip, the less accurate the heuristic.

A max limit of 30,000 expanded nodes was set in experiments. With the most difficult uncertainty level ($\sigma^2 = 6400$), Dublin instances are solved in 90.2% cases, Rome instances are solved in 98% cases, and the Montpellier success rate is 99.3%. (The 8am, $\sigma^2 = 6400$ subset shows a reduction of the Dublin success rate to 76.7%.) In successful cases, the average search times in seconds, measured on a 2.7GHz Ubuntu machine, are: 0.05 ($\sigma^2 = 0$), 0.30 ($\sigma^2 = 1600$) and 0.64 ($\sigma^2 = 6400$) for Dublin; 0.01, 0.08 and 0.18 for Rome; and 0.004, 0.02 and 0.05 for Montpellier. A more detailed discussion is beyond the scope of this paper.

Conclusion

We have presented a focused empirical study comparing standard, deterministic plans with uncertainty-aware contingent plans. We have found that, often, contingent plans can provide a better worst-case arrival time, which is important in cases when a deadline must be observed (e.g., arrive at the airport in time). Our study provides evidence in favour of switching from deterministic to contingent planning.

In future work, we plan to consider the possibility of missing a bus because the bus is too crowded, and to focus on specific origin and destination areas.

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