Context-Aware Travel Support During Unplanned Public Transport Disturbances

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Abstract: This paper explores the possibilities and challenges of realizing a context-aware travel planner with bidirectional information exchange between the actor and the traveller during unplanned traffic disturbances. A prototype app is implemented and tested to identify potential benefits. The app uses data from open APIs, and beacons to detect the traveller context (which train or train platform the traveller is currently on). Alternative travel paths are presented to the user, and each alternative is associated with a certainty factor reflecting the reliability of the travel time prognoses. The paper also presents an interview study that investigates PT actors' views on the potential use for actors and travellers of new information about certainty factors and travellers' contexts, during unplanned traffic disturbances. The results show that this type of travel planner can be realized and that it enables travellers to find ways to reach their destination, in situations where the public travel planner only suggests infeasible travel paths. The value for the traveller of the certainty factors are also illustrated. Additionally, the results show that providing actors with information about traveller context and certainty factors opens up for the possibility of more advanced support for both the PT actor and the traveller.

1 INTRODUCTION

Smartphones create new opportunities within Public Transport (PT) to both provide the traveller with more personalized information, and give the traveller possibilities to share their own information with the PT actor. For instance, information shared by the traveller about where the traveller currently is located can be used by the PT actor to improve transport services (Stelzer et al., 2016). If this type of bidirectional information exchange is used for transmitting real-time information during unplanned traffic disturbances, both the passengers' decision basis for the continued journey and the PT actors' decision basis for disturbance management can be improved. Previous research shows that information about disturbances and alternative travel paths is highly prioritized by the travellers (Currie och Muir, 2017; Hörold et al. 2014). Moreover, the travellers prefer to get this information on an individual level (i.e. specified according to the individual travel plan), rather than on aggregated level (for instance, an overview of all traffic disturbances within an area) (Hörold et al. 2014). Previous research also shows that information from the traveller has the potential to improve the PT actors' decisions and actions, especially in traffic management (Mayas et al. 2015).

The primary aim of this study is to investigate potential benefits for actors providing PT services and travellers, of travel/journey planners that are context-aware och enable bidirectional information exchange between the actor and the traveller, during unplanned traffic disturbances. A secondary aim is to explore the possibilities and challenges of realizing such a travel planner, including demonstrating potential benefits, through a prototype implementation. The main purpose with the study is to increase knowledge of how the support for both travellers and PT actors can be improved, when decisions have to be made due to unplanned traffic disturbances. Thereby, a more attractive public transport and increased system efficiency may be obtained (e.g. through more efficient disturbance management and improved resource utilization).

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The study includes three parts: interviews with PT actors, development of a prototype in the form of an app, and app tests in different scenarios. The interviews investigate the potential use for actors and travellers of new information about certainty factors associated with travel times, as well as the potential use for actors of information about travellers' contexts and travellers' destinations, based on bidirectional communication with the traveller (e.g. via an app). The app development part investigates if and how this type of context-aware travel planner can be developed, and enables scenario tests. It also explores how certainty factors associated with travel times can be developed and implemented in a travel planner. Finally, the scenario tests are used to study the effects in travel time and travel alternatives presented to the traveller, when using the existing app versus the new prototype app during unplanned disturbances in the south of Sweden. The interviews encompass different types of traveller context information; thereby, they cover a broader area than the app development and tests, as the app only considers contextual information related to which train or train platform the traveller is currently on, in combination with traveller destination.

The prototype app is developed independently from current travel planner apps, but its functionality is, in a longer perspective, intended to be integrated with existing travel planners. The app operates as follows. In the event of a traffic disturbance, the traveller is given the opportunity to request personalized information through the app. This request also means that the traveller agrees to share information with the PT actors about his/her desired destination and current context (i.e. which train or train platform the traveller is currently on). The destination is provided manually by the traveller whereas the context is detected by the app, i.e. it detects current train or platform instead of the geographical position, which is common for regular travel planners. This means that the alternative travel paths provided to the traveller can be based on future train stops, instead of the train stations or bus stops that the train is currently close to but that may be impossible to reach due to the itinerary of the train. Based on the traveller's destination and context, as well as disturbance information and timetables from open APIs, the app provides suggestions for alternative ways to continue the journey. Each travel alternative is associated with a certainty factor reflecting the reliability of the travel time prognosis, based on time and the reason for the disturbance. The travellers can thus choose between the different travel alternatives based on the certainty of the different travel alternatives and their personal needs. Thereby, a more informed decision about continued travel can be made. This type of certainty factor can also serve as a support for traffic managers and traffic informants.

The main differences between the focus of this study and the existing solutions commonly used today are:

1. The prototype app is context aware and is thereby able to provide the traveller with personalized information about alternative travel paths, in particular during unplanned traffic disturbances (e.g. advising the traveller to alight at the next stop and then catch another bus/train).
2. PT actors get access to information about the travellers' contexts and their destinations, which can be used in disturbance management.
3. Travellers and PT actors get access to certainty factors, which are based on time and the reason for the disturbance, for the travel time prognoses. These certainty factors can be used both in disturbance management and by the travellers to make more informed decisions during unplanned traffic disturbances.

The remainder of the paper is organized as follows. Section 2 provides an overview of the related work. Section 3 describes the methodology used for the interviews, the prototype development and the scenario tests. Section 4 presents the results and in section 5, the conclusions are drawn and discussed.

2 RELATED WORK

Over the years, travel planners have evolved from only presenting static information to the traveller, to also including real-time and predicted information. This development can be mainly attributed to the widespread use of smartphones and technological advancements. In particular, the introduction of real-time information related to traffic disturbances has been of great importance to travellers. However, there are also other types of real-time information that can be incorporated into a travel planner. For instance, Georgakis et al. (2020) present the implementation of a travel planner for MaaS schemes that includes dynamic constraints (e.g., available on-demand service offers with different estimated time of arrivals).

There are a few travel planners on the market that try to estimate the traveller context. For instance, Czech train operator České Dráhy has developed a "context-aware" app that suggests alternative routes during disturbances, in order to ease train travel during the upgrade of the Czech railway system to ETCS. The app relies on purchased tickets to discover with which train the passenger travels (Tomášek 2021). Within research, there are several research studies presenting different methods for detecting a traveller's transport mode (Sadeghian et al. 2021; Stenneth et al. 2011). There are also studies that predict the travellers' contexts on an aggregate level. For instance, Benchimol et al. (2021) predict future passenger flows at stations and onboard trains. This information is then used by a travel planner that incorporates the predictions as criteria, meaning that the predictive load information is not only shown to the traveller as information, but also used as a search criterion when trip alternatives are identified by the travel planner. Most studies focusing on passenger flow predictions use data from different types of local readers, cameras or sensors (e.g., automated fare collection or automatic passenger counting technologies). However, other types of data have also been investigated, for instance, from social media (Zhu et al. 2017).

As for information exchange between the operator and the traveller, connected to travel planning support, it is common to only use the GPS position and personal preferences. For instance, Esztergár-Kiss (2019) provides an overview of European travel planners, with a particular focus on multimodality, and presents a framework for evaluation of such travel planners. Notably, none of the studied travel planners include travel context beyond the personal preferences related to the trip (e.g., maximal number of transfers or preferred transport mode) and GPS coordinates. However, some conceptual work has been done to identify what context information related to a traveller can be used for improving travel support. In particular, Jevinger and Persson (2019) investigate how the traveller's current context can be utilized in the travel planner to provide better support during unplanned disturbances.

Thus, we have failed to find previous research that utilizes context information in terms of which train or train platform the traveller currently is on, to improve the travel planner.

There are a lot of research studies on different ways of predicting arrival times and replanning traffic in case of delays within PT (e.g., Josyula (2020), Xu and Ying (2017)), but significantly fewer studies on how to estimate (and communicate) the certainty of such predictions. Many of the studies that do exist, base their estimations on statistical methods (O'Sullivan et al. 2016; Rahman et al. 2018). In particular, O'Sullivan et al. (2016) have an approach that is similar to ours. They view estimated arrival times from traveller information systems as black boxes, and calculate prediction intervals based on historical data of estimated arrival times, combined with actual outcome (i.e., the actual arrival times). However, their study does not take the causes of the traffic disturbances into account.

Studies with other objectives than estimating prognosis certainty, often make statistical assumptions on the certainty to illustrate something else (e.g., how such certainties can be communicated or used in travel planning) (Botea and Braghin, 2015; Fernandes et al. 2018). For instance, Botea and Braghin (2015) assume that the certainty of arrival is normally distributed with mean value 0 and standard deviation 80 seconds or 40 seconds. This is then used to develop stochastic itineraries that, unlike ordinary itineraries with sequentially arranged transport routes, may include several route alternatives, taking into account potentially missed connections.

Naturally, there are also several studies that apply optimization or machine learning to estimate both arrival time and certainty (Coffey et al., 2011; Yu et al., 2017). For instance, Yu et al. (2017) use Relevance vector machine to estimate the arrival time of buses, as well as lower and upper bounds for this, based on confidence intervals. The outcome is then compared with five other traditional machine learning methods.

In summary, to the best of our knowledge there is a lack of understanding of how a travel planner that uses information about the traveller's context can be developed and what the potential benefits may be. There is also a need for increased understanding of the potential use for actors and travellers of new information related to certainty factors, travellers' contexts and travellers' destinations. Additionally, while there are studies estimating certainty in arrival time prognoses in PT, we have failed to find studies that base these estimations on the actual disturbance reasons. This study aims to address these research gaps.

3 METHODOLOGY

3.1 Interviews with PT Actors

The interviews focused on what information is available today about the traveller's context and destination, and how certainty in travel time prognoses is calculated, as well as how new information about these things could be used and affect travellers and actors (see interview questions in

Appendix). The interviews were semi-structured, and since they took place during the Corona pandemic, they were conducted over a digital communication platform (Microsoft Teams).

The following officials were interviewed:

- Organizational developer within rail traffic information, at the Swedish Transport Administration
- Project manager within traffic information, at the Swedish Transport Administration
- IT architect with focus on traffic information, at Skånetrafiken (the regional public transit authority in the south of Sweden)
- Organizational developer within traffic information, at Skånetrafiken
- Head of travelling staff, at SJ Öresund (a Swedish railway company operating in the south of Sweden)
- Traffic informers (two persons), at the Swedish Transport Administration

The IT architect and the Organizational developer at Skånetrafiken were interviewed together, and the Traffic informers were interviewed separately, i.e. in total 6 interviews were conducted. Two researchers asked questions and took notes during each interview. After each interview, the notes were compiled and sent to the respondent for validation. The majority of the respondents returned with a confirmation of correctness, while a few returned with clarifications and corrections, which were added to the compilations.

3.2 Prototype Development

There are different ways to detect which train or platform a traveller is currently on, that do not require any active participation from the traveller. Today's travel planners often detect the traveller's physical position through GPS, and then search for nearby PT stops. This solution could be used to detect the train station a traveller is currently on; however, for the onboard and platform situations, other solutions are necessary. One way for the onboard situation is to map the train GPS position with the traveller's GPS position. By using an algorithm for this type of GPS mapping from previous research (see e.g., Stenneth et al. 2011), the current train could be revealed. In the south of Sweden, many trains are equipped with GPS; however, depending on operator, the open APIs lack real-time positioning data for some of them. Moreover, there might be a time delay between the train positioning data and the traveller positioning data, which may cause mapping problems.

Another solution may be to use a personal area network technology to detect which train a traveller is currently on, for instance, Bluetooth from fixed beacons installed onboard the train or a wifi network open to the passengers onboard a train. With appropriate software, the MAC address of an onboard wifi router could be identified, and with a mapping between trains and MAC addresses, the current train could be detected. However, such a mapping is not available today in the Swedish open APIs. Alternatively, if the wifi transmitted information about the current train, the app could easily just pick this information up. However, this type of information is not available as a pure data string. Another problem that concerns both GPS and wifi is that it might be difficult to separate two trains standing next to each other.

In this study, we chose to use fixed Bluetooth Low Energy (BLE) beacons. The beacons broadcasted the physical train ID or platform ID, which was picked up by the prototype app. The physical train ID was mapped to the line the train was currently running on (using the open APIs). The advantages with this solution are that, thanks to the short coverage of BLE, it is easier to separate two nearby trains. Moreover, the open APIs do contain a mapping for many operators, which makes this solution possible. The drawbacks are that beacon installations and battery changes/power cord installations are required, which entails costs.

For the calculation of certainty factors, the Swedish Transport Administration provided us with three sets of traffic disturbance data covering three months: July 2021, December 2021 and February 2022. Thereby, potential season variations were accounted for. The data included reason code (i.e., the cause of the disturbance), announced time (i.e., time of departure/arrival according to timetable), reporting time (i.e., time when new prognosis was announced) and the error margin of the prognosis (i.e., difference between prognosis and actual departure/arrival as an absolute value). As our access to disturbance data was limited, while the data needed to be extensive enough to provide credible results, the study only focused on the reason codes that appeared more than 1000 times in the data files. For the others, only the mean value of the error margin of the prognoses were calculated. Initial regression analyses on the different variables above showed significant relations between reason code, error margin of the prognosis, and time interval between reporting time and announced time. Therefore, we chose to focus the certainty factor calculations on these variables. The calculations included mean values of the error margin of the prognoses, given different time intervals between reporting time and announced time, together with prediction intervals and determination coefficients. In those cases where the lower bound of a prediction interval was negative, it was set to zero, since the error margin is at least zero (we only focus on the difference between prognosis and actual departure/arrival as absolute values).

3.3 Scenario Tests

The scenario tests focused on disturbances in the rail traffic between Lund central station and Malmö central station, in the south of Sweden. The main reason for selecting this stretch of track is that it is considered a bottleneck in Swedish rail traffic. A large number of travellers (and freight transports) use this stretch daily (up to 60,000 travellers per day according to Skånetrafiken (2020)), and unplanned disruptions thereby create major problems. In addition, there is a relatively large range of alternative travel routes around the stretch.

During a period of four weeks, four researchers manually monitored the traffic between these two stations. For all major disturbances, searches for trips were made using both the existing public travel planner and the new prototype app.

4 RESULTS AND ANALYSIS

4.1 Interviews with PT Actors

The findings from the interviews related to the information available today, can be summarized as follows.

Regarding the currently available information about the *traveller's destination and context*, the results show that the actors work with estimates of the number of travellers on trains, and that they have relatively little information about the traveller's destination and other contexts. The traveller estimates are often based on the onboard staff's manual calculations, onboard ticket validations or registration of activated tickets in the travel planner app, and they are used to provide the traveller with congestion forecasts or to facilitate evacuation, if needed. The information from travel tickets often reveals which zones a traveller is crossing, but usually not which route and departures the traveller has chosen. The Swedish Transport Administration also has cameras installed on certain train platforms, which are activated when needed. These cameras are used to, for instance, verify that the travellers seem to have understood, and thus reacted to, certain traffic announcements, e.g., about track change. The cameras are sometimes also used to manually estimate how many travellers are on a platform. Information about travellers in wheelchairs or with bicycles/wheelchair/etc. may be manually collected through observation by the onboard staff (unless a special seat ticket, e.g., for a wheelchair, has been booked). This information is sometimes transmitted via telephone to the train dispatcher, for traffic planning purposes.

Regarding how *certainty in travel time prognoses* is calculated today, the results show that the Swedish Transport Administration has relatively good knowledge of which prognoses are certain and which are uncertain. However, the certainties are not quantified, but primarily based on the personal experiences of the staff. For instance, it is often possible to state with greater reliability when a missing train driver will arrive, than to state how long will it take for traffic to recover from people illegally crossing rail tracks (which usually involves police action). As a consequence of the uncertainty, the actors are a bit restrictive in communicating less reliable prognoses to the traveller. There is a risk that the traveller perceives prognoses as promises, and when they are broken, frustration and demands for compensation may arise. In order to give some expression to certainty in prognoses, a number of keywords are used in the communication with the traveller, e.g., "departs at the earliest", “preliminary time” and “await time” (used when awaiting a time when the train will run again). The keyword will be removed when there is a more reliable time prognosis.

The findings from the interviews related to how new information about certainty in travel time prognoses, traveller's context and traveller's destination, could be used and affect travellers and actors, are shown in Table 1.

In summary, the interviews show that the PT actors today work with estimates of the number of passengers on trains, and their knowledge of which prognoses are certain or uncertain are primarily based on the personal experiences of the staff. Information about the travellers’ destinations can only be obtained for those who have chosen to buy a ticket that specifies the entire journey. This means that information about the commuters’ destinations is usually not available. In addition, the actors lack other contextual information beyond what can be visually observed by the onboard staff, e.g., different types of disabilities. The information at hand for the on-board staff is only to a limited extent distributed to relevant actors.

Table 1: Interview results.

Information	Use and effects
Traveller's destination and the train or train platform the traveller is currently on	Traffic track planning (to minimize distance and time for travellers when changing trains)
	Train prioritizations (e.g., prioritizing a full train over a relatively empty train)
	Estimation of time for boarding and alighting, which can be used for early prediction and communication of delays
	Improved train-replacement traffic planning in terms of route and vehicle capacity, e.g. taxi to places that few travellers go to and many direct large buses to places that many travellers go to
	Improved evacuation
	Long-term traffic planning
Quantified certainty in travel time prognoses	Improved support to the traveller in assessing different transport alternatives
	Earlier prognoses provided to the travellers (as they will not interpret them as promises)
	Improved actor support when communicating disturbances to travellers (as the certainty is quantified)
	Facilitated work for new employees with little experiences of estimating certainties
	Improved planning of staff (e.g. customer service) and activated communication channels (during large disturbances)
Many travellers with many/big suitcases	Traffic track planning (to minimize distance and time for travellers when changing trains)
	Estimation of time for boarding and alighting, which can be used for early prediction and communication of delays
Travellers with bicycles/ wheelchair/ etc.	Early information to the traveller about lack of space on planned train (requires technology for detecting empty onboard space/seats)
	Ordering of train-replacement traffic that allows for bicycles/ wheelchair/etc.
	Traffic track planning (to minimize distance and time for travellers when changing trains, and to have a working elevator or no stairs)
	Estimation of time for boarding and alighting, which can be used for early prediction and communication of delays
Traveller disabilities (e.g. vision or hearing impairment)	Improved support both during disturbances and in normal situations (e.g. help with finding correct seat, information about which trains or carriages are less full, verification that traveller has boarded the correct train)
	Improved evacuation

With the help of the app described above, information about a traveller's destinations and whether the traveller is on a particular train or platform, can be obtained. Table 1 shows that this type of information, together with certainty factors for alternative travel routes, can be useful for a range of different situations, for both travellers and actors.

4.2 Prototype

4.2.1 Architecture and Design

Based on the detected train or train platform that the user is currently on, as well as the end destination as specified by the user, several travel plans are generated. These are found using the Resrobot Route Planner API, an open API that includes all Swedish PT operators. If the user is on a train, travel plans are created from every upcoming station for that train. If the user is standing on a platform, travel plans are simply created with that station as the origin. In order to also find suppressed travel paths, i.e., paths that according to the original timetables have longer travel times than the most time-efficient travel paths, different manipulations, such as excluding trains in the search, were applied. If the used traveller planner API would have used the most updated prognoses when finding the travel paths, this would not be necessary. The found travel plans are then updated with data on delays and cancellations in the train traffic, received from the open API provided by the Swedish Transport Administration ("Trafikverket"). If any leg in a travel plan is cancelled, or its arrival time is delayed beyond the departure time of the next leg (assuming a three-minute minimum transit time between legs), that travel plan is filtered away. Due to a lack of real-time data on delays and disturbances for other modes of transports than train, only timetable times are used for transport legs with bus. Of the remaining plans, the ones with an arrival time at the final destination that is closest in time, are presented to the user. The app allows the user to save one of these plans, so that it can be viewed later even when the user is not on a train or platform.

The server side of the application was implemented in Java as a Spring Boot application, while the front-end was created using the Apache Cordova framework and implemented in Javascript, HTML and CSS. Figure 1 shows the final system architecture and Figure 2 shows how the app operates.

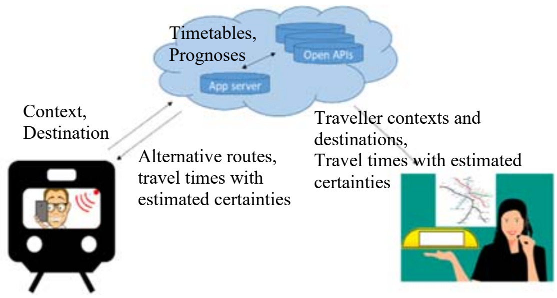

Figure 1: System architecture of the app prototype.

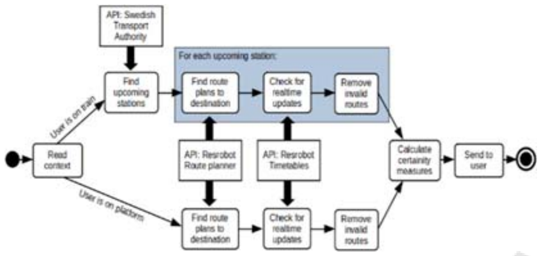

Figure 2: Flow chart illustrating how the app operates.

4.2.2 Certainty Factors

As mentioned above, this study only focused on the reason codes that appeared more than 1000 times in the provided data files. This criterion was fulfilled by 11 disturbance reason codes (see Table 2). These reason codes represent disturbances related to accidents, unexpected dwelling times, delayed connecting trains, priorities of other trains, track errors and other infrastructure failures. The regression analysis on the error margin of the prognosis in relation to the time interval between reporting time and announced time, for the different reason codes, showed that the F values and the P values were less than 10^{-11} for all the reason codes. This means that there is a clear correlation between the error margin of the prognosis and the time interval between reporting time and announced time. Table 2 shows the results of the statistical analysis. Column three shows the determination coefficients (r^2), columns 4 to 7 show the mean error margins of the prognoses and the corresponding 80% prediction intervals, when the time intervals between the reporting time and announced time are 10 min. and 40 min., respectively. The determination coefficient indicates how much of the variation in the error margin can be explained by the different time interval between reporting time and announced time, whereas the 80% prediction intervals are intervals within which the error margins lie with an 80% probability, given the different time intervals between the reporting time and the announced time.

As can be seen, the prediction intervals are different for different reason codes. For ONA – and OUT 01, the intervals are 23.88 and 10.32 minutes, respectively, when the time intervals between the reporting time and announced time are 10 min. The same pattern can be seen when the time intervals between the reporting time and announced time are 40 min. This means that the reason code, i.e., the reason for the disturbance, has a relatively large impact on how certain a given prognosis is. Access to information about the reason code can thus provide support in estimating the reliability of prognoses during unplanned disturbances.

Table 2: Statistical analysis of certainty factors.

Reason code	**#data entries**	**Deter. coeff.**	**10 min. report-ann.**		**40 min. report-ann.**	
			Mean	**Pred.**	**Mean**	**Pred.**
DPR 03	8091	0.13	3.83	0-10.72	5.82	0-12.70
DPS 01	1610	0.08	4.30	0-12.68	6.05	0-14.43
IBÖ 01	2263	0.25	5.46	0-17.83	7.39	0-19.77
IBÖ 02	1368	0.10	4.54	0-10.89	6.57	0,21-12.92
JTP -	1817	0.04	4.37	0-16.67	6.59	0-18.89
JTP 13	1066	0.13	3.74	0-17.14	7.11	0-20.52
OMÄ 02	1885	0.11	6.14	0-13.97	8.56	0.73-16.40
OMÄ 03	1087	0.10	4.99	0-11.52	6.69	0.15-13.23
ONA -	1452	0.11	9.61	0-23.88	13.35	0-27.62
OUT -	3043	0.06	5.09	0-15.15	7.20	0-17.27
OUT 01	2446	0.18	4.68	0-10.32	8.63	2.99-14.28

A comparison between columns 5 and 7 in Table 2 shows that the prediction intervals are slightly larger when the time intervals between the reporting time and announced time are 40 min. than when they are 10 minutes. This result indicates, together with the determination coefficients in Table 2, that some part of the variations in the error margin can be explained by the time interval between the reporting time and the announced time. This means that access to information about the time interval between the reporting time and the announced time can also provide support in the estimation of the reliability of prognoses during unplanned disruptions.

4.3 Scenario Tests

Figures 3 and 4 show an example of the differences between the public travel planner offered today to people traveling in the south of Sweden, and our prototype app, when an unplanned traffic disturbance means that the traveller is likely to miss the next connection. Figure 3 shows the interface of the public travel planner when searching for a trip between two cities (Kritstianstad C and Svedala station) during this traffic disturbance. In this scenario, the traveller has already boarded the train 1103 from Kristianstad C. The app suggests that the traveller changes train in Lund C. However, train 1103 is expected to arrive to Lund C after the train to Svedala has already departed (at 20:29 and 20:25 respectively). Thereby, this itinerary will probably not be feasible.

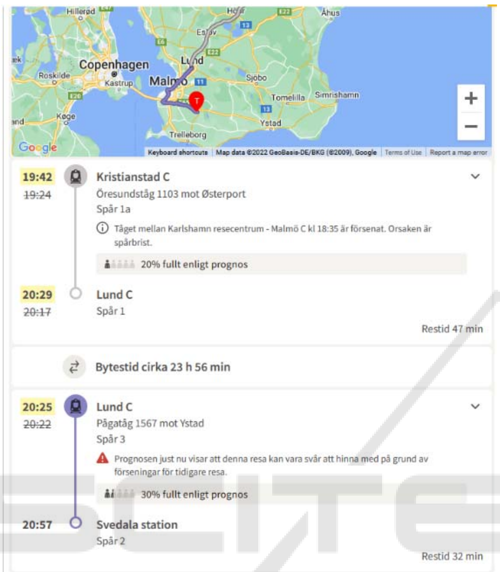

Figure 3: Public travel planner interface when searching for a trip from Kristianstad C to Svedala station, during an unplanned disturbance.

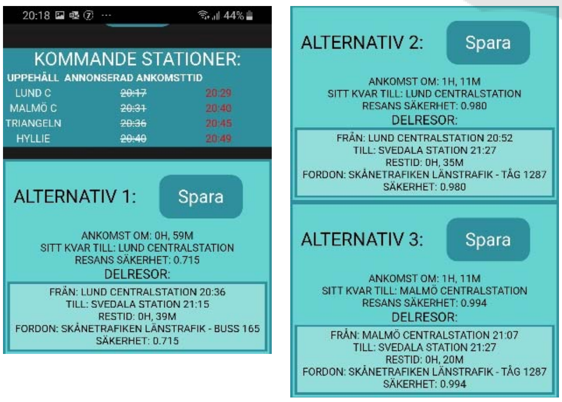

Figure 4: The suggested alternative travel paths in the prototype app, during the unplanned disturbance shown in Figure 3.

Figure 4 shows the interface of our prototype app during the same traffic disturbance. This app presents three alternative itineraries with different certainty factors. Alternative 1 suggests switching from train to bus 165 in Lund C. This bus departs 7 minutes after the train's estimated arrival in Lund. Based on historical data on certainty in prognoses for this type of disturbance, the calculated certainty factor for this travel alternative is 0.715. This means that at the time of the search, the probability that the sum of the given prognosis and the prediction interval is less than the time available for changing vehicles (including 3 minutes for walking between vehicles) is 0.715. If it had been closer to 1, choosing this alternative would have been safer. Alternative 2 suggests changing to train 1287 in Lund C. Alternative 3 also suggests switching to train 1287, but in this case in Malmö C instead. The certainty factor becomes higher in both of these alternatives, since they involve longer exchange times between arrival and subsequent departure.

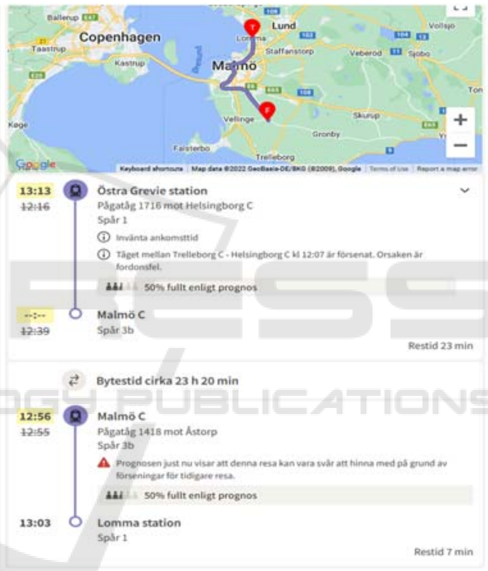

Figure 5: Public travel planner interface when searching for a trip from Östra Grevie station to Lomma station, during an unplanned disturbance.

Figures 5 and 6 show an example of the differences between the public travel planner and our prototype app, when an unplanned traffic disturbance causes upcoming stops of the train the traveller is on, to be cancelled. In this scenario, the traveller is currently on train 1716 and is going from Östra Grevie station to Lomma station. Figure 5 shows that the public travel planner suggests traveling via Malmö C. However, since the train is cancelled for the last stops, it will never arrive at Malmö C. This itinerary will thereby not be feasible. Our prototype app shows three alternative travel routes, see Figure 6. All travel routes include train 1420 and their certainty factors are of the same magnitude. What separates the travel routes is where the traveller gets off the current train and gets on train 1420.

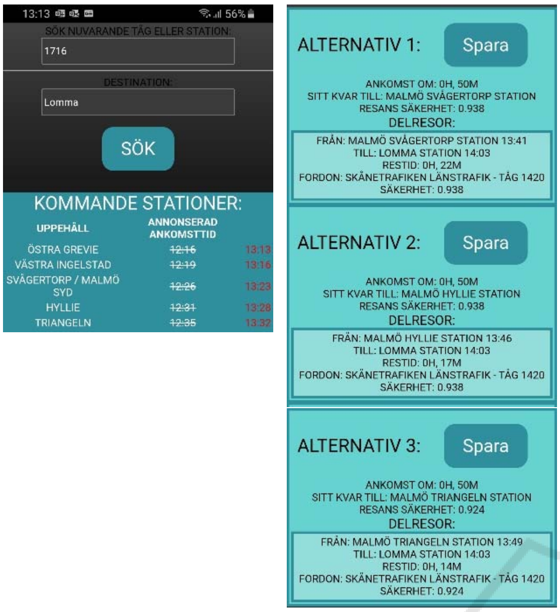

Figure 6: The suggested alternative travel paths in the prototype app, during the unplanned disturbance shown in Figure 5.

The above examples show how the prototype app, through knowledge of the traveller's destination and context (in this case which train the traveller is currently on), can provide an updated itinerary that is difficult for the traveller to identify using the public travel planners. The examples also illustrate the value for the traveller of providing certainty factors connected to different travel alternatives.

5 DISCUSSION AND CONCLUSIONS

This paper has shown that a travel planner detecting the traveller's context has the potential to provide better support for both the traveller and PT actor (given that the traveller is willing to share context information), by extracting relevant information that enable better decision making, during unplanned disturbances. Furthermore, the potential of using disturbance reason codes to make better estimates of the reliability of the travel time prognoses, has also been shown.

The interviews with PT actors showed that the actors today work with estimates of the number of passengers on trains, and that their knowledge of which prognoses are certain or uncertain are primarily based on the personal experiences of the staff. Information about the travellers' destinations can only be obtained for those who have chosen to buy a ticket that specifies the entire journey, i.e., this information is usually not available for commuters. The interviews also showed that providing the actors with information about the travellers' destinations, which train or train platform a traveller is currently on, and other types of contextual information (such as disabilities), opens up for the possibility of more advanced support for both the PT actors and the travellers. Certainty factors associated with different alternative travel paths may also be of value for both actors and travellers.

The prototype development showed how a travel planner with bidirectional information exchange between the actor and the traveller, that is aware of the traveller's context (in this study which train or train platform the traveller is currently on), and that presents alternative travel paths with associated certainty factors during traffic disturbances, can be realized. In particular, the study showed how these certainty factors can be calculated based on information about the reason for the traffic disturbance.

Finally, the paper illustrated what types of benefits such a travel planner may provide for the traveller. The updated itineraries presented for the user takes into account the traveller's personal context and destination, and suggests travel paths that are not provided by the public travel planner used today. In particular, the study showed that with this new type of travel planner, the traveller can find ways to reach the destination, when the public travel planner only suggests infeasible travel paths. The value for the traveller of different certainty factors connected to the travel alternatives was also illustrated.

As mentioned in Section 4.2, there is a lack of open real-time data on delays and disturbances for other modes of transports than train, in the south of Sweden. Thereby, the certainty factors and the context awareness developed in the travel planner prototype, only focus on trains. Ideally, it should incorporate more transport modes. However, the methods developed in this study for estimating certainty factors and for obtaining context awareness may be applied to other PT transport modes as well, if data can be made available.

The new type of travel planner presented in this study may be used by the PT actor to collect information about the amount of passengers onboard different trains or on different train platforms. However, the collected data will only represent a fraction of the passengers, since all may not be interested in using the travel planner. This fraction can potentially be estimated based on how many travellers use the travel planner in general, which may enable a more stable number of passengers onboard or at platforms. However, the more travellers who choose to use the app, the more reliable information can be achieved.

Furthermore, this study has not considered any additional costs or tickets that might be needed when switching routes within the public transport network. In the south of Sweden, zone-based tickets are often applied, which means that this is usually not a problem. However, in other context this may need to be considered.

For future studies, we believe it would be interesting to investigate how other transport modes can be added (e.g. taxi, bicycle, bus). It would also be interesting to study how the context awareness could be expanded to other environments (e.g. home, on the way to a bus stop).

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APPENDIX

The interviews were conducted as follows. First, the project was introduced for the respondents, and the concept of uncertainty factors was explained. Then, the respondents were asked to describe their previous and current professional roles and associated tasks. Thereafter the following questions were asked:

1. Concerning the information about the travellers that is available for you today:
    a. What information do you have about the traveller’s destination and which train or train platform a traveller is currently on?
    b. What other types of traveller context information do you have access to?
2. If you do not have access to information about the traveller’s destination and which train or train platform a traveller is currently on:
    a. How could such information be used?
    b. What effects do you think this would have on travellers and PT actors?
3. Concerning any additional information about the traveller’s context that you would like to have access to:
    a. How could such information be used?
    b. What effects do you think this would have on travellers and PT actors?
4. Concerning information corresponding to uncertainty factors in prognoses that is available for you today:
    a. What type of information do you have access to, if any?
    b. How is this information used?
5. If you do not have access to information corresponding to uncertainty factors:
    a. How could such information be used?
    b. What effects do you think this would have on travellers and PT actors?