An Activity-Based Multimodal Model Structure to assess Transportation Management Strategies for Urban Emergencies

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Abstract—There are many kinds of disasters that can severely impact the transportation system of an urbanized region. Transportation authorities therefore need to develop management strategies to adequately deal with such emergencies. In this paper, we discuss the structure of a simulation model that can be used to assess a candidate strategy. We model the choice behavior of the population during the emergency using a microscopic, activity-based approach and simulate the performance of the multimodal transportation network with a macroscopic dynamic network loading module, taking into account what happens on a normal day. The disaster plan under consideration may contain adaptive elements and is assessed in a robust way by testing a range of possible scenarios.

Index Terms—Urban emergencies, transportation, choice models, activity-based models, multimodal dynamic network loading, robust optimization.

I. Introduction

In today's world, there exist many types of disasters that can have severe impacts on the transportation systems of urban areas. One can think of a variety of both natural and man-made disasters, such as floods, hurricanes, wildfires, tsunamis, large-scale traffic accidents, airplane crashes, industrial accidents, nuclear disasters and terrorist attacks. These disasters can be characterized by substantial delays to everyday traffic, by presence of evacuation traffic leaving the affected area or sheltering in-place, by emergency services trying to reach the disaster site or by combinations of the above.

As the transportation systems of urbanized regions typically have a low capacity compared to the number of citizens living and working there, they can easily become overloaded by the surge in travel demand and/or reduction of available capacity. This necessitates authorities to have proper transportation management strategies in place to deal with such situations adequately. While developing a strategy, a simulation model can obviously be a valuable tool for the assessment of the impacts of various candidate strategies in various disaster scenarios.

In order to construct a simulation model to assess the effectiveness of an emergency management strategy, one can identify three main components that are required. First of all, the interface with the transportation management problem must be defined, such that the management strategy of authorities can be tested and optimized. Secondly, the decision-making behavior of the human beings in the system must be identified: one cannot effectively manage the transportation system if one is unable to predict what travel choices will be made. Finally, one needs a method to determine the consequent network performance and travel times. The remainder of this paper discusses each of these three components in more detail.

II. Defining the Management Problem

Before we can assess a management strategy, the problem must first of all be defined from the perspective of authorities. For authorities, their disaster management problem can be formulated as an optimization problem, consisting of an objective or goal function, a set of constraints and a set of decision variables. Each is discussed below.

A. Objective

Although various objectives are possible in any case, the objective differs fundamentally between evacuations and other emergencies. For non-evacuation emergencies, a typical objective is to minimize delays for the travelers. For evacuations, one may for example maximize the number of evacuated people within a certain time limit, or one may minimize the evacuation time or network clearance time, i.e. the time required to evacuate the population or a specified percentage of that, or one may minimize the total time people spent in the area at risk, representing exposure [1]. Eventually it will be up to the authorities to decide how they define their objective, depending on the nature of the emergency.

Emergencies are relatively rare events and planning thus, even with a well-calibrated model, has to deal with uncertainty regarding various aspects of both transportation supply and demand. Taking this into account can avoid constructing overly optimistic disaster plans [2]. We will therefore use a robust evaluation technique, where one evaluates the goal function for a set of scenarios, possibly randomly sampled, thereby deriving a worst-case effectiveness or a probability distribution of the effectiveness of the disaster plan [3].

B. Constraints

In addition to constraints that relate directly to particular traffic management measures, there are constraints relating to the disaster management plan as a whole. For non-evacuation emergencies, one obvious constraint is that the quality and safety of a rescue operation must meet particular minimum thresholds: the transport system should be optimized, but this optimization must not significantly hinder the rescue operation. For evacuations, a similar constraint can be present, although in this case it is also possible to include the trade-off directly in the objective, since both the evacuation and the rescue processes relate to the safety of the public.

C. Decision variables

The decision variables that the authorities can use to steer the situation in the desirable direction, can be divided into operational, tactical and strategic variables. We use these different categories to be able to construct adaptive disaster plans, that allow achieving a higher worst-case performance when uncertainty is taken into account.

Operational variables can be frequently changed real-time, in some cases even autonomously by a computer, potentially as advanced as network-wide model-predictive control. Examples are traffic light and ramp metering settings, dynamic speed limits, the control of peak-hour and contraflow lanes and information shown on dynamic route information panels and provided through public transport announcements. Manual traffic control, such as by traffic regulators, and deployment of emergency services also fall into this category. The disaster plan prescribes what circumstances change the operational variables in what way.

Strategic variables cannot change as frequently and are hence fixed in the disaster plan. By still allowing infrequent changes, they can be turned into tactical variables. Examples are departure advise, mode advise, destination advise, route advise, deployment of roadblocks, usage of contraflow roads, construction of temporary roads, availability and schedule of public transport and provision of public shelter facilities.

III. Modelling Travel Choices

Our second component models the choice behavior of the people in the system. This serves two main purposes. Firstly, it allows to predict which number of people are expected at what location in the network, at what time and with what mode they travel, such that the disaster plan can properly accommodate the expected loads on the system. As a consequence, this also allows to forecast the progress of an evacuation over time. Secondly, understanding the choice behavior also means that one understands how authorities can influence these in order to improve the conditions in the transportation system, which is one component of the emergency management strategy. As illustrated by Hurricane Rita, lack of such understanding can seriously deteriorate the transportation network [4].

For travel choices in normal situations, it has long been recognized that the demand for trips is actually derived from the demand to undertake activities at different locations [5,6]. By modelling activity patterns rather than individual trips, one can for example consider resource (e.g. vehicle) and task allocation within households, whether household members travel together, how activities are dynamically rescheduled, and the corresponding consequences for the load on the transportation system.

When applied in the context of emergencies, this means that an activity-based model can predict where members and vehicles of a household are in the network and what people are doing at the moment an emergency event starts, as a function of the time-of-day. Naturally, this is important information for managing the emergency, since these are the initial conditions. Such a model also tells what people would intend to do if there were no emergency or if they are unaffected by the emergency, so that ‘background traffic’ is automatically included. We therefore opt for an activity-based approach, implying that our choice model will be of microscopic nature.

This leads to a ‘model of escalation’, consisting of three basic states a household can be in:

1. In the first state, which is the initial state for all households, travel and activity plans are conducted as usual. As long as all households are in this state, the transportation system is considered to be in user-equilibrium.
2. In the second state, households notice they are affected by the unusual situation and adapt their activity and travel plans to cope with the experienced or anticipated travel delays. This ranges from simply switching routes to rescheduling all activities. The potential gain from making a change may be balanced against the (mental) effort required to implement it [7,8].
3. In the third state, a household either evacuates or seeks shelter. Obviously, this third state is only relevant for emergencies that pose a danger to the public at large, and it requires that the danger is acknowledged and acted upon [9]. In this state, the activity-based approach can predict how household members gather and prepare to evacuate together [10], e.g. including making necessary preparation purchases [11], which has important implications for traffic flows [12].

The choice model that is used, should be dynamic in nature, so that the development of the emergency situation over time can be analyzed, subject to the availability of information to the decision-maker at that point in time. Each decision is therefore a function of what happens on a normal day, the characteristics and risk attitudes of the households, their decisions on a normal day as well as what happened during the emergency event so far. This allows for high flexibility with respect to the formulation of the choice model. Figure 1 shows an example how such a choice model can be structured at the household level.

IV. Simulating Network Performance

The last step in building the model is to model the transportation network performance that results from the choices that both people and authorities make. Like the choice model, the network loading algorithm must be dynamic,

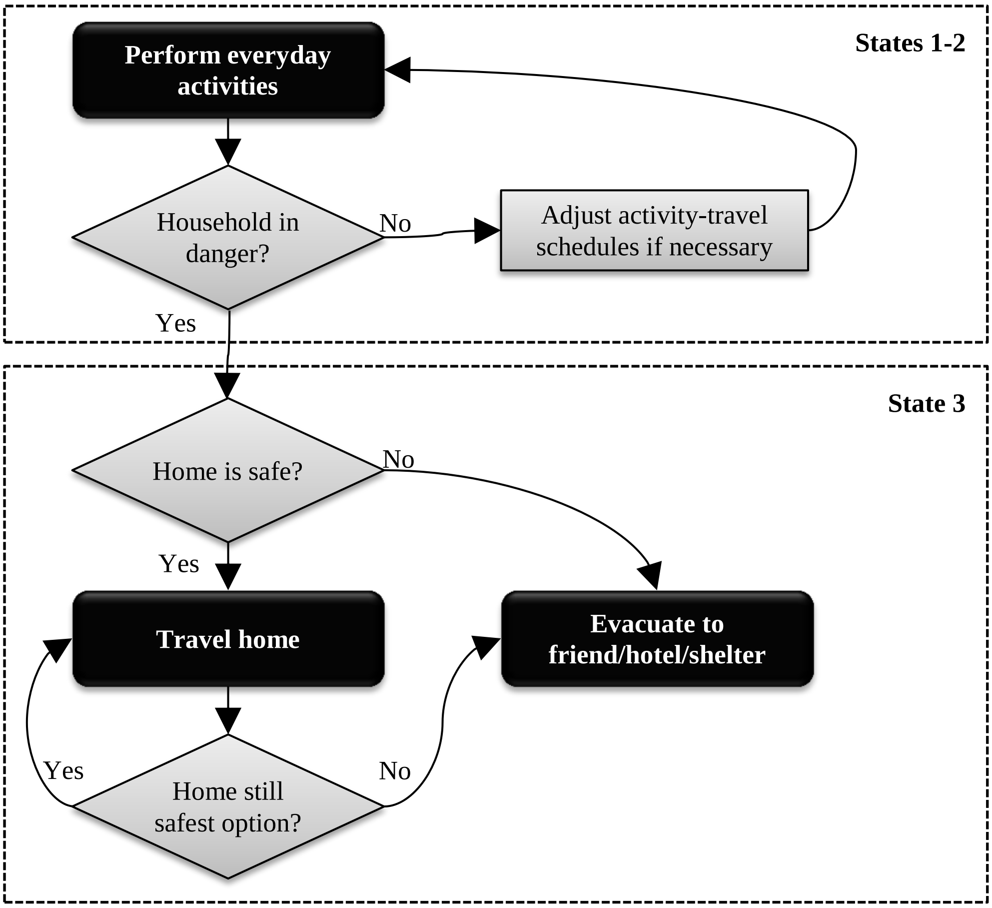

Fig. 1. Example flow-chart for a household-level activity-based choice model for the behavior of household members during an emergency situation.

because an emergency situation is not static [13]. Furthermore, particularly for urbanized regions, multiple modes of travel need to be supported, so that public transport and pedestrian traffic can be included [14]. Hence, we will opt for a multimodal dynamic network loading module.

A key decision to make is whether the network simulation will be microscopic or macroscopic, i.e. whether it will be based on individual vehicles (and pedestrians) or aggregate flows. Since we opted for a microscopic choice model, it may seem straightforward to use microscopic network simulation as well, but this has some important drawbacks. Firstly, a traffic propagation model based on individual vehicles is significantly more computationally expensive, which can become particularly cumbersome for large-scale events like hurricane evacuations. Secondly, and perhaps more importantly, microscopic models require a large amount of input parameters to represent driving behavior. However, our current empirical knowledge of how an emergency situation changes driving behavior, is basically limited to longitudinal behavior only [15], and this may even further change due to e.g. adverse weather conditions and heavy vehicle loads [4,16]. Because of this lack of knowledge, we prefer a macroscopic representation of traffic as that can be more parsimonious, does not necessarily require microscopic data for calibration and has a higher computational efficiency.

A. Interaction with the Choice Component

Using a macroscopic dynamic network loading component with a microscopic choice component, means that the interaction between both components needs some attention. Both serial and parallel execution can be used to realize this:

- Serial execution can be used to find a user-equilibrium solution for a normal day. One runs the choice component, yielding dynamic route demand that is input to the network loading component, yielding dynamic travel times that are input to the choice component, and so on [17]. The method of successive averages [6] can be adapted to find the equilibrium: one can randomly freeze the choices of an increasing fraction of the households in each iteration to simulate flow averaging, eventually yielding household choices that reproduce the equilibrium situation.
- Parallel execution can be used to simulate a disaster scenario. While the network simulation component is running, one can already determine dynamic travel times up till the current time. We can use this property to track household members throughout the network,

so that we repeatedly alternate between the network loading component and the choice component as time progresses. The results for the normal day equilibrium can serve as input to the choice component used here, so that the system remains in equilibrium until the emergency situation starts disturbing it.

Together, these methods allow for first modelling a normal day and next modelling how the disaster disturbs such a day. Unlike the normal day choice model, this does require the disaster response choice model to be causal, which is a realistic assumption as full knowledge about the future is not yet available in this case [18]. Hence, no user-equilibrium is used for the disaster scenario. Both execution methods are depicted in Fig. 2.

Although serial execution can be used for the disaster scenario as well [17], parallel execution skips the construction of intermediate infeasible solutions where some people depart for their next trip before they arrived from their previous trip. The absence of iterations makes this method a lot more efficient. Of course, parallel execution does require the software of both model components to be tightly integrated so that the model can rapidly alternate between them.

V. Conclusion

In this paper, we proposed a simulation model structure that can assess the effectiveness of a transportation management strategy for an emergency. This proposed model structure contains three main components: an activity-based, microscopic choice model for the behavior of households in the network, a multimodal, macroscopic dynamic network loading model that is used to simulate the consequent network performance and travel times and an overall interface for evaluating adaptive disaster plans in robust way. By embedding the combined components in an optimization framework, robust and adaptive disaster plans can be created for effectively managing urban transportation networks in a wide range of emergency events.

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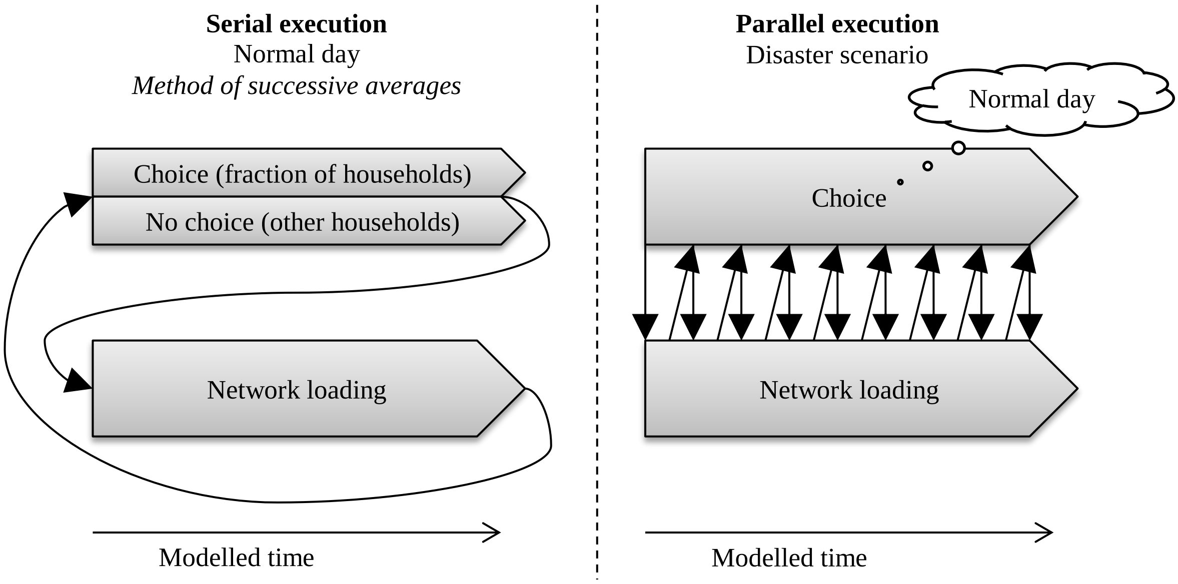

Fig. 2. Flow charts of both methods of execution for the overall model. In both cases, the choice component supplies route demand to the network loading component, whereas the network loading component supplies travel times to the choice component.

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