Framework to Evaluate Rescheduling due to Unexpected Events in an Activity-Based Model

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ABSTRACT The concept of rescheduling is essential to activity-based modeling in order to calculate effects of both unexpected incidents and adaptation of individuals to traffic demand management measures. When collaboration between individuals is involved or timetable based public transportation modes are chosen, rescheduling becomes complex. This paper describes a new framework to investigate algorithms for rescheduling on a large scale. The framework explicitely models the information flow between traffic information services and travelers. It combines macroscopic traffic assignment with microscopic simulation of agents adapting their schedules. Perception filtering is introduced to allow for traveler specific interpretation of perceived macroscopic data and information going unnoticed; it feeds person specific short term predictions required for schedule adaptation. Individuals are assumed to maximize schedule utility. Initial agendas are created by the FEATHERS activity-based schedule generator for mutually independent individuals using an undisturbed loaded transportation network. The new framework allows both agent behavior and external phenomena to influence the transportation network state; individuals interpret the state changes via perception filtering and start adapting their schedules, again affecting the network via updated traffic demand. The first rescheduler investigated uses marginal utility that monotonically decreases with activity duration and a monotonically converging relaxation algorithm to efficiently determine the new activity timing. The current framework implementation can support re-timing, re-location and activity re-sequencing; re-routing however is the subject of future research.

INTRODUCTION AND MOTIVATION

A simulation framework for evaluation of rescheduling algorithms has been built. The initial schedule (agenda) for every inhabitant of Flanders (Belgium) is generated by the FEATHERS activity-based model described in Bellemans et al. (*1*). The new WIDRS (Within Day Re-Scheduling) framework is a software tool to evaluate schedule adaptation by individuals due to changed conditions. This project is part of our research efforts concerning dynamic activity-based simulation (parts of which are implemented by the well-known agent-based-modeling software technique). Changes in available schedule execution time are considered; those can originate from unexpected traffic or weather conditions but can also follow from negotiations between individuals about departure or arrival times during collaborative (cooperative) scheduling (e.g. while carpooling for commuting trips). The project is aimed at large scale simulations used to investigate traffic demand management (TDM) measures.

WIDRS consists of two main interwoven components: *schedule adaptation* (rescheduling) and *schedule execution*.

Rescheduling can be done by adapting activity execution start time or duration (*re-timing*), by choosing an alternative location (*relocation*), by selecting a new activity order (*resequencing*) and by dropping or inserting activities. This paper describes the framework built and the *utility-based (de)compressor type* rescheduler used in the first experiments.

RELATED RESEARCH

The problem of rescheduling activities in daily agendas has been investigated by several research groups.

On one hand, mechanisms describing the rescheduling process itself have been developed. Arentze et al. (*2*) present the comprehensive *Aurora* model developed in Joh (*3*) for dynamic activity-travel rescheduling decisions. *Aurora* is based on S-shaped utility functions. The maximal utility value is a product of functions modeling the attenuation by start time, location, position in agenda and delay since last execution of the activity. Bounded rationality agents are assumed. Gan and Recker (*4*) present a mixed integer programming formulation of the HARP problem (Household Activity Rescheduling Problem). Jang and Chiu (*5*) describe a model that uses a quadratic utility function and integrates the scheduler with a dynamic traffic assignment tool DynusT. A similar approach has been taken by Bekhor et al. (*6*) who integrated the Tel-Aviv activity-based model with the MATSim toolkit allowing for re-timing and re-routing.

On the other hand, factors influencing rescheduling characteristics for specific activities can be determined from surveys. van Bladel et al. (*7*) point out the difficulties to estimate the utility function parameters and show the S-shaped dependence of the utility on the delay since the preceding execution of a same activity. van Bladel et al. (*8*) use mixed logit models with random effects to estimate the effect of several factors on rescheduling. In a similar way, Guo et al. (*9*) describe a web-based tool to acquire stated preference data to uncover the (re)planning process. Roorda and Andre (*10*) use an MNL model to uncover the factors that determine the choice between several rescheduling options after a well-defined unexpected delay.

FRAMEWORK CONCEPTUAL OVERVIEW

The WIDRS framework overview is shown in Figure 1.

1. The upper right block shows the initialization step. FEATHERS is used to generate a schedule for each member of the synthetic population; those schedules represent the

planned agendas for mutually independent individuals using an undisturbed transportation network. Those initial daily plans are assumed to be optimal i.e. generating maximal utility.

2. The framework is based on traffic flows between traffic analysis zones (TAZ). Macroscopic SUE (stochastic user equilibrium) traffic assignment is used to apply the traffic demand derived from the microsimulated schedules to the transportation network. Microscopic routing is not supported (hence no microscopic *re-routing*). This decision is motivated by the desire to limit the simulation runtime. Travel times are skimmed and made available in *impedance matrices*. The impedance matrix used by the FEATHERS activity-based modeling scheduler to establish the initial agenda for each individual, holds for the normal case (without any incident). OD-pair specific peak load factors are applied in FEATHERS to account for travel during morning and evening peaks respectively.

3. Network state can change at discrete moments in time only; *network state evaluation* by individuals is limited to those moments (called *NSE-moments*). The interval between them is called the *NSE-period*. NSE-moments define the time resolution for individuals to experience modified congestion effects. This makes it possible to integrate macroscopic network state modeling with microscopic agent behavior modeling. Note that other time related phenomena (activity/trip start times, durations, notification times) all can be modeled by WIDRS using a finer grained time resolution. Network state is determined only after each NSE-period because the required traffic assignment calculation is computationally expensive. NSE-moments are separated by a 15[min] interval.

4. Before the actual simulation, 96 impedance matrices for 15[min] equidistant moments in time are determined by skimming the minimal travel times between TAZ (traffic analysis zone) centroids under normal traffic load. Those serve as the base reference. During the simulation, similar matrices are derived for the same moments in time for the case where the network is loaded with traffic generated by adapted schedules.

5. In order to apply an incident, the capacity on a given set of network links is reduced by a given factor for a given period of time: this is called *network disturbance*. During the simulation, a new impedance matrix is calculated using the actual traffic load at each NSE-moment taking the time dependent network capacity into account.

6. Agents can get notified at any moment in time after the incident start time. As a consequence, an agent can get *notified* before starting a trip that contains some affected network links: such individual is called an *informed individual*. Those persons become aware very soon of the network travel times disturbance. Others only become aware after having suffered from congestion (too late to avoid congestion so that they need to reschedule any remaining activities anyway). Individuals getting aware of congestion *by experience* are called *non-informed individuals*. Each individual can decide to adapt their schedule immediately after becoming aware of congestion. Note that *being informed* relates to a *(person,trip)* tuple. This allows for modeling individuals using the network while they are informed about additional delay for a specific subset of trips

only. An individual can be both *informed* with respect to zero or more trips while at the same time being *non-informed* about zero or more other trips.

7. Individuals who got stuck on the network due to congestion, become aware of being delayed, at equidistant moments in time only. In our first experiments, this is assumed to be sufficiently realistic as long as *NSE-period* is not longer than 15[min]. At those moments in time, the affected individuals estimate the actual distance driven and the remaining distance and duration to drive. A new estimate for the total travel time is calculated: at this point, the modeled agents compare the most recent estimate of the effective travel duration to the previous one. This is where the modeled individual senses the positive or negative difference in travel duration and, where appropriate, decides to reschedule. Agents deciding to reschedule based on sensed difference between estimated travel times, are the non-informed experiencing individuals mentioned in section Framework Conceptual Overview item 6.

8. There is no iteration to some equilibrium over a single day because no information about the future shall be made available to the individual as a source for learning. Each individual makes her/his own prediction (interpretation) about the near future. An individual can learn from her/his reaction to the perceived incident but the acquired knowledge can only be used to estimate delays for future possibly similar (but not identical) incidents.

9. The study area covers Flanders (Belgium). It is modeled by 2386 traffic analysis zones (TAZ) with an average area of about $5[km^2]$. TAZ are bundled into 319 municipalities.

10. The set of persons affected by network disturbance is determined as follows. A set of (unidirectional) network links is selected for capacity reduction (in order to mimic an incident by network capacity disturbance). Three cases are considered: off-peak, morning-peak and evening-peak. For those cases, TransCAD is used to calculate the shortest time to travel between each pair of municipality centroids (m_0, m_1) under the network load predicted by FEATHERS. This is done for both the undisturbed and the disturbed networks and the maximum of the pairwise differences is kept in the *worst-effect-matrix*. Each (m_0, m_1) pair for which the corresponding element in the worst-effect-matrix exceeds a given threshold is an affected OD-pair. Every individual traveling an affected OD-pair is an affected individual.

11. The first framework implementation simulates the evolution of one day; hence there is no individual memory and no learning mechanism.

RESCHEDULER CONCEPTS

1. Individual behavior is modeled by perception filtering: this accounts for *lack* of information and personal *interpretation* of the information that becomes available. The latter is the individual interpretation of the uncertainty with respect to the travel times registered in the impedance matrices for the NSE-moments; those matrices represent the data made available via traffic information services (TIS). The base impedance matrices (see section Framework Conceptual Overview item 4) are considered to represent common knowledge about the expected travel times. The excess travel time calculated for the

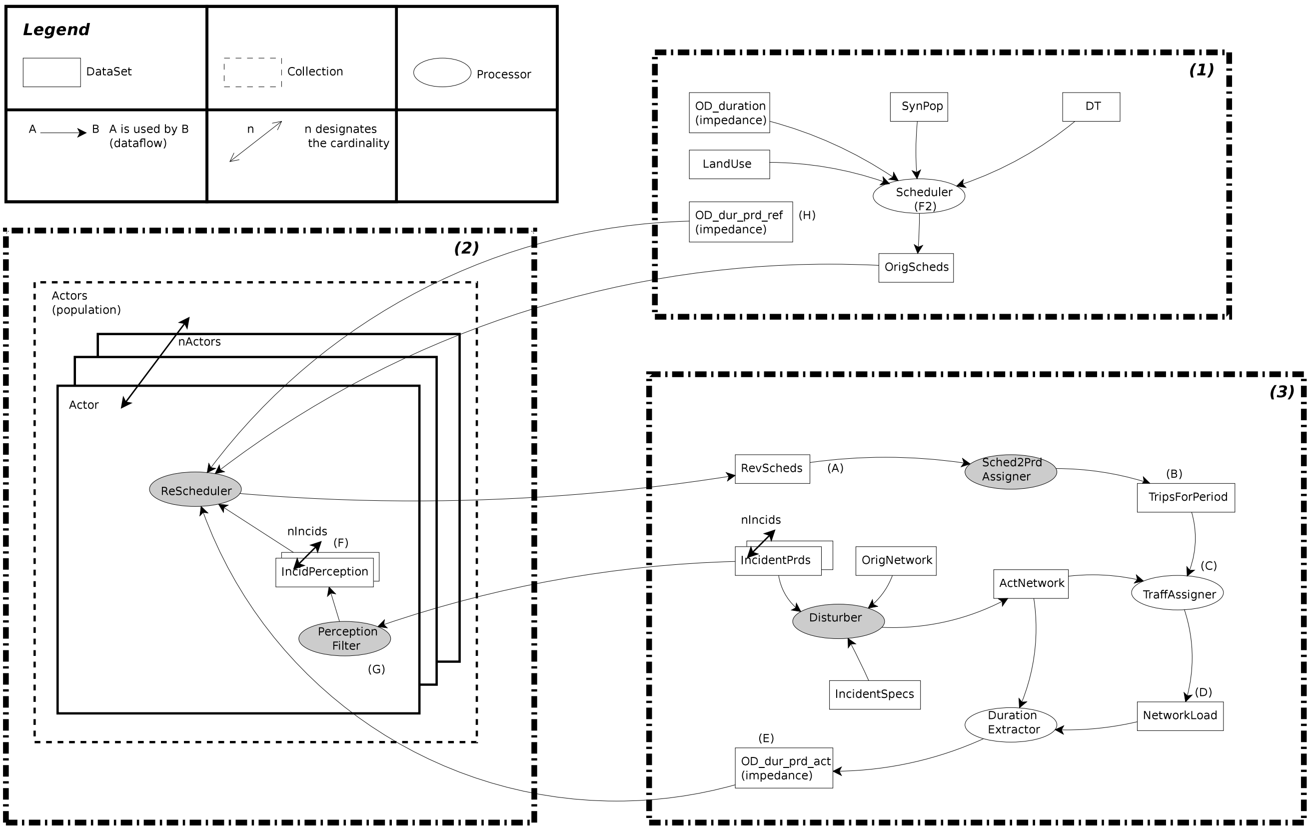

FIGURE 1 : **Simulator overview. Block (1) shows the FEATHERS activity based model that produces initial schedules for the synthetic population members from landuse data, travel surveys and an impedance matrix. Block (2) shows the microsimulator part consisting of *perception filtering* and *rescheduling*. Block (3) shows the macroscopic simulator consisting of *traffic assignment*, *impedance matrix extraction* and *network disturbance* application.**

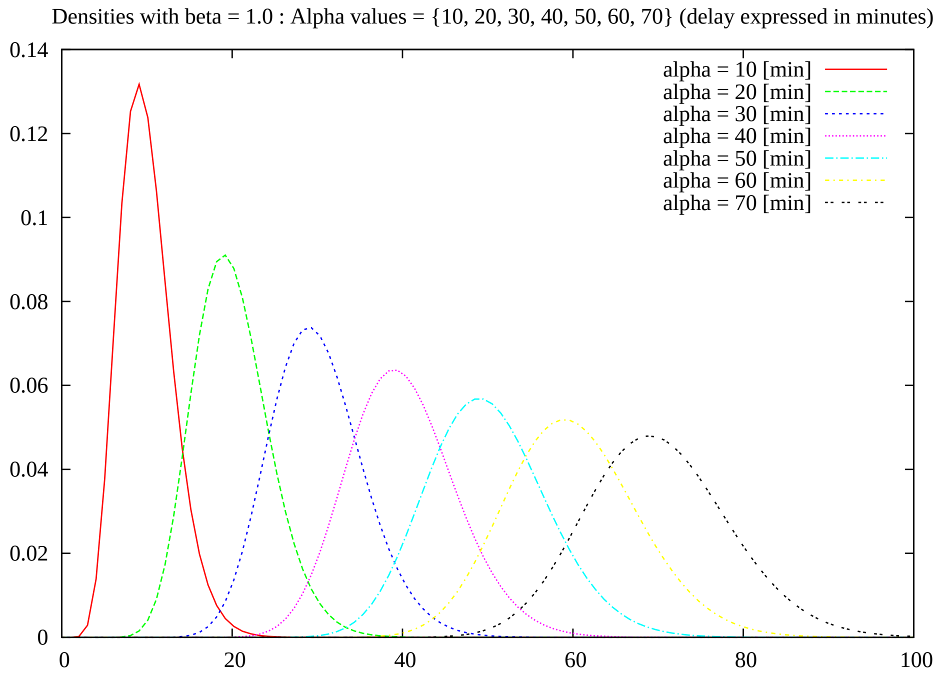

FIGURE 2 : Gamma probability densities for delay values estimated by individuals when traffic information service predicts an expected value of 10[min] ...70[min] for congestion duration. The rate factor $\beta = 1.0$ (scale factor $\theta = \frac{1}{\beta}$ = 1.0) for each case.

congested situation is considered to be the expected delay made available by the traffic information service. It is interpreted (biased) by each individual in a specific way.

2. Individuals are assumed to behave in a rational way and to try to maximize their utility by executing activities. As a consequence, in case of modified predicted travel times, they will adapt their schedules. Adapted schedules in turn result in a modified network load and travel times for the future *NSE-period*s.

3. Individuals behave mutually independent.

RESCHEDULER MODEL : TOPICS RELATED TO TIMING

The framework has been used to run simulations by means of a first simple utility based rescheduler. This section explains how timing and duration phenomena influence the behavior of the simulated individual.

Modeling delays

1. Gamma distributions using scale factor $\beta = 1.0$ are used to model delays. Both the expected value (mean) and variance are given by α.

$$f(x;\alpha,\beta) = \begin{cases} \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} & x > 0; \alpha > 0; \beta > 0 \\ 0 & x \leq 0 \end{cases} \tag{1}$$

Sample density functions are shown in Figure 2

2. Gamma distributions have been chosen because of the *reproductive property* (the sum of independent gamma distributed variables with α_1, β and α_2, β is gamma distributed with $(\alpha_1 + \alpha_2), \beta$ which is useful when processing accumulating delays).

Incident awareness offset

Both the information *dissemination* mechanism and the probability for *assimilation* by the individuals are essential model components.

1. Two dissemination models are considered. The first is the *broadcast* model which is a volatile push mechanism which means that the information sender is the initiator and the message can get lost; radio broadcast information is an example. The second is the *publish* model where the information consumer either subscribes and receives a non-volatile message or decides to consult a (web)service; in this case the information can be consulted multiple times at arbitrary moments in time. Both the time at which an individual gets notified and the levels of information loss and distortion, depend on the mechanism used.

2. No evidence about individual behavior in this respect was available while implementing the initial model. Hence for the experiments, the *broadcast* model is assumed and assimilation probability equals one for each affected individual and zero for everyone else. The delay between incident occurrence and broadcast (notification delay) is assumed to be gamma distributed $\omega_{not} \sim gamma(\alpha_{\omega_{not}}, \beta)$ with an expected value of $\alpha_{\omega_{not}} = 30[min]$. A single gamma density function is used to sample the value for the notification delay. As a consequence, every individual gets informed but many of them too late (those are not informed in time to be able to use the information).

3. Integration of the *publish* mechanism is required if it turns out that individuals having alternative routes to a destination tend to consult TIS before starting to execute the trip and hence show substantially different behavior.

4. Agents getting notified before making use of congested network links, are *informed individuals*. The other ones are *non-informed individuals*.

Expected traveltime adaptation and perception filtering

Perception of (the effect of) incidents by individuals is modeled by

1. for *informed* individuals (who are notified in time)
   (a) the time lag ω_{not} between the incident occurrence and the individual becoming aware of it by traffic information
   (b) the incident effect duration δ_{not} as expected by the individual
2. for *non-informed* individuals (who learn by experience)
   (a) the *NSE-moment* in time t_{exp} at which the person experiences a non-expected delay while traveling (hence a delay that adds to the expected daily congestion)
   (b) the person specific estimated duration δ_{exp} to finish the ongoing trip

Expected incident effect duration

1. Early notifications (both by *broadcast* or *publish* mechanisms) can come available before the incident (effect) end time. Hence, the incident effect duration is not known and each individual needs to estimate it along with the level and duration of its effect on travel times. It is assumed that the TIS provides in direct or indirect way some data about the kind of the incident which is used by the individual to estimate the duration. In the current model, the duration of the specified network disturbance is used as the expected value for a gamma distributed stochastic from which each individual samples to estimate the disturbance effect duration.

2. Following cases are distinguished :

   (a) Case awareness by notification : the event duration as perceived by an individual who gets notified by a TIS, is modeled by a gamma distributed stochastic $\delta_{not} \sim gamma(\alpha_{\delta_{not}}, \beta)$. δ_{not} models the duration expected by each individual aware of the incident and is based on the individual's personal conviction: as a consequence, a new value is sampled for each individual (who is aware of the incident). Note that even in case an individual gets notified while traveling, the new travel duration cannot be fetched from the impedance matrix in use because that does not contain information about the future.

   (b) Case awareness by experience : the incident effect duration as perceived by an uninformed person who experiences the incident effect by getting stuck in a congestion, is modeled by a *gamma* distributed stochastic $\delta_{exp} \sim gamma(\alpha_{exp}, \beta)$. The individual is assumed to be able to predict (probably by experience) the new travel duration (impedance) for the OD-pair (s)he is using at the NSE-moment in time at which (s)he becomes aware of the problem. The individual believes that the remainder of the trip will be driven at *congested speed* because that is, at that moment, the best estimate for the duration to travel from origin to destination. Note that this belief can get revised at the next NSE-moment. Let d_{rem} be the duration required to travel the remaining distance; that is recalculated for each non-informed individual at each NSE-moment. The uncertainty is modeled by sampling the duration to travel the remainder of the trip distance from a gamma distribution with expected value d_{rem}.

$$E(remDur) = \frac{\alpha_{exp}}{\beta} = d_{rem} \tag{2}$$

$$\delta_{exp} \sim gamma(\beta \cdot d_{rem}, \beta) \tag{3}$$

3. Using a more elaborated model, the *incident effect duration estimation* can be made dependent on the drivers history (experience) which in turn can be assumed to grow with age.

Particular moments in time with respect to rescheduling

1. Let t_{inc} be the time at which the incident occurs.

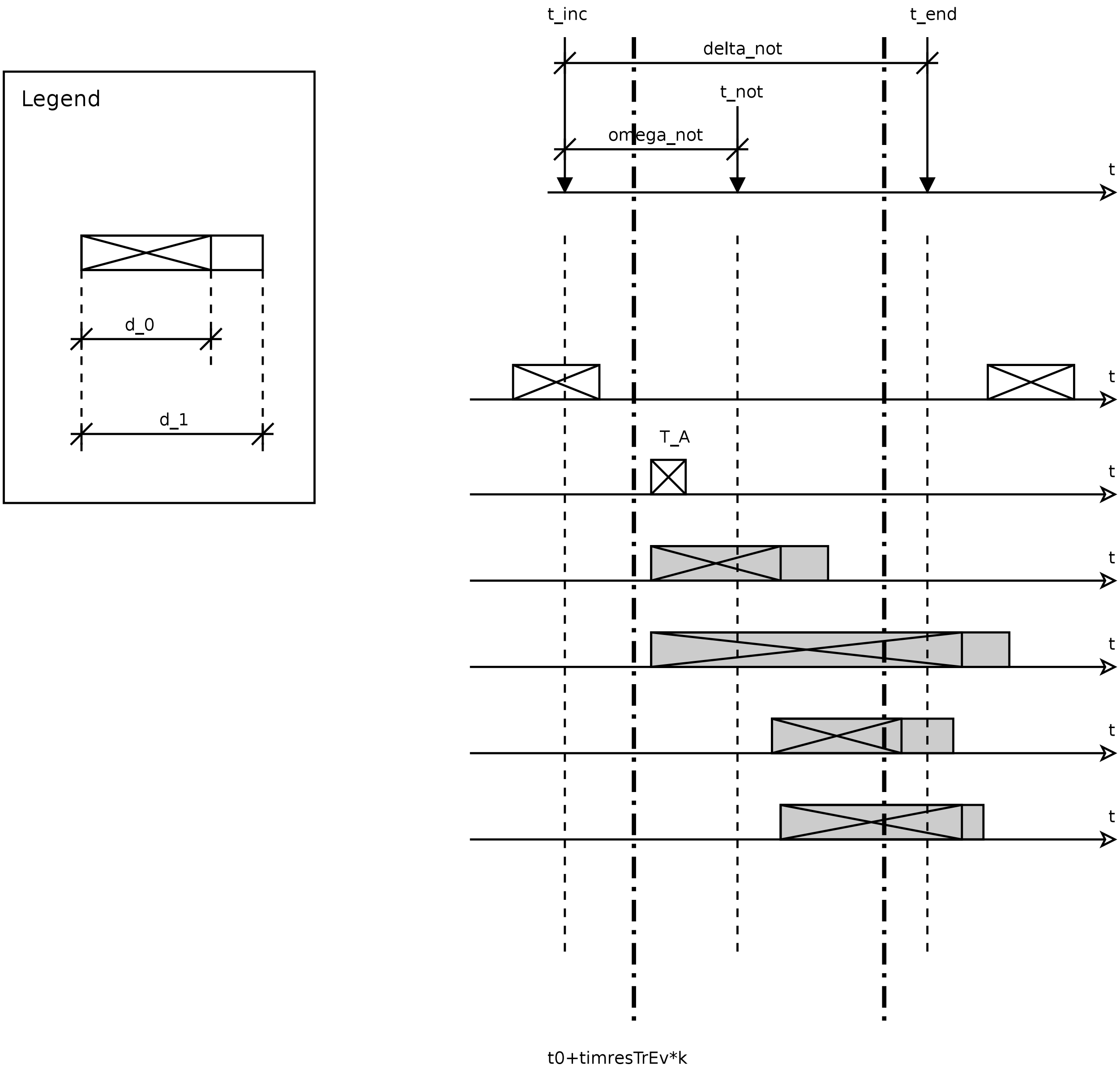

FIGURE 3 : ***Awareness by notification : informed person*. A rectangle designates a trip. d_0 is the original duration, d_1 is the new duration. t_{inc} is the incident start time, t_{not} is the time at which the person gets notified and t_{end} is the expected incident effect end time. Trips ending before t_{not} are not affected. Note that the duration for trip T_A is unaffected because the trip is too short to get the incident effect *experienced* or *notified*. Grey blocks represent affected trips that induce rescheduling due toe timely notification. Dash-dot lines represent NSE-moments at which network state change can be perceived by individuals.**

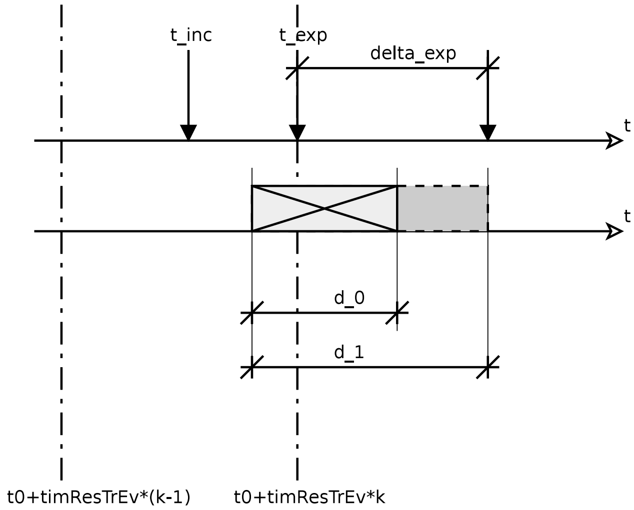

FIGURE 4 : ***Awareness by experience : nonInformed person*. Incident occurs at t_{inc} and ends later than t_{exp}. The value for δ_{exp} is drawn from a gamma distribution whose mean equals the travel duration calculated using the actual network state. Dash-dot lines represent NSE-moments at which network state change can be perceived by individuals.**

2. Case *awareness by notification* : see Figure 3

   (a) The individual gets informed before experiencing the incident effect.

$$t_{not} = t_{inc} + sample(gamma(\omega_{not}, 1.0)) \tag{4}$$

$$t_{end} = t_{inc} + sample(gamma(\delta_{not}, 1.0)) \tag{5}$$

   where
   t_{not} : is the time at which the individual gets notified (informed)
   t_{inc} : is the incident occurrence time
   t_{end} : is the incident's effect end time as estimated by the individual. Note that $t_{end} < t_{not}$ is possible (i.e. the person gets informed after the incident effect is expected (by this person) to have terminated).
   ω_{not} : is the expected delay between the incident start and the notification
   δ_{not} : is the expected incident effect duration

   (b) Note that we assume that the person knows the incident start time (at least as soon as (s)he gets informed): in reality, the incident occurrence time is not always contained in the traffic info conveyed.

3. Case *awareness by experience* : see Figure 4.
   The (traveling) person becomes aware by experiencing delay: this always occurs at equidistant discrete times because only at those moments the network state is recalculated. Relevant moments in time are given by

$$t_{exp} = t_0 + k \cdot \Delta_{NSE}, k \in \mathbb{N} \tag{6}$$

$$t_{end} = t_{exp} + \delta_{exp} \tag{7}$$

where

- t_{exp} : is the NSE-moment at which the individual evaluates the situation
- t_0 : is the simulated period start time
- Δ_{NSE} : is the *NSE-period* duration
- t_{end} : is the incident's effect end time as estimated by the individual. Note that $t_{end} < t_{not}$ is possible (i.e. the person gets informed after the incident effect is expected (by this person) to have terminated).
- δ_{exp} : is the duration of the incident effect as estimated by the individual

4. The rescheduling algorithm is run

   (a) at each *NSE-moment*: for each affected individual traveling at that moment in time a new *trip end time* estimate comes available. The current implementation calculates a new schedule only at the last *NSE-moment* contained in the trip. This is sufficient because individuals are assumed to act independently. As soon as interaction between individuals has been implemented, rescheduling at least shall be condidered for each *NSE-moment* in order to model information flowing from delayed individuals to people who they need to cooperate with during the remainder of the schedule. As soon as an individual becomes aware of any delay while knowing that her/his agenda requires collaboration with someone else, information about the expected delay can be forwarded to the cooperators.

   (b) at each notification moment for informed individuals

   (c) at each trip end (arrival) time

RESCHEDULER MODEL : UTILITY FUNCTIONS

The first experiment serves to evaluate both the framework and a simple rescheduler when operating on a large set of individuals and using a countrywide real road network.

General Assumptions

1. It is assumed that the schedules predicted by FEATHERS are optimal (i.e have maximal utility).

2. The rescheduler only covers *re-timing*, no activity dropping, nor activity reordering, nor activity relocation, nor mode changes.

3. Utility does not depend on absolute time as long as the activity is performed within the specified time limits.

Utility Function

1. Marginal utility $v(d)$ is assumed to monotonically decrease with activity duration d. Utility $u(d)$ is determined by integration and by requiring zero utility for zero duration. Subscript i identifies the activity. Both are shown in Figure 5

$$v_i(d) = k_i \cdot e^{-\alpha_i \cdot d} \tag{8}$$

$$u_i(d) = (1 - e^{-\alpha_i \cdot d})\frac{k_i}{\alpha_i} \tag{9}$$

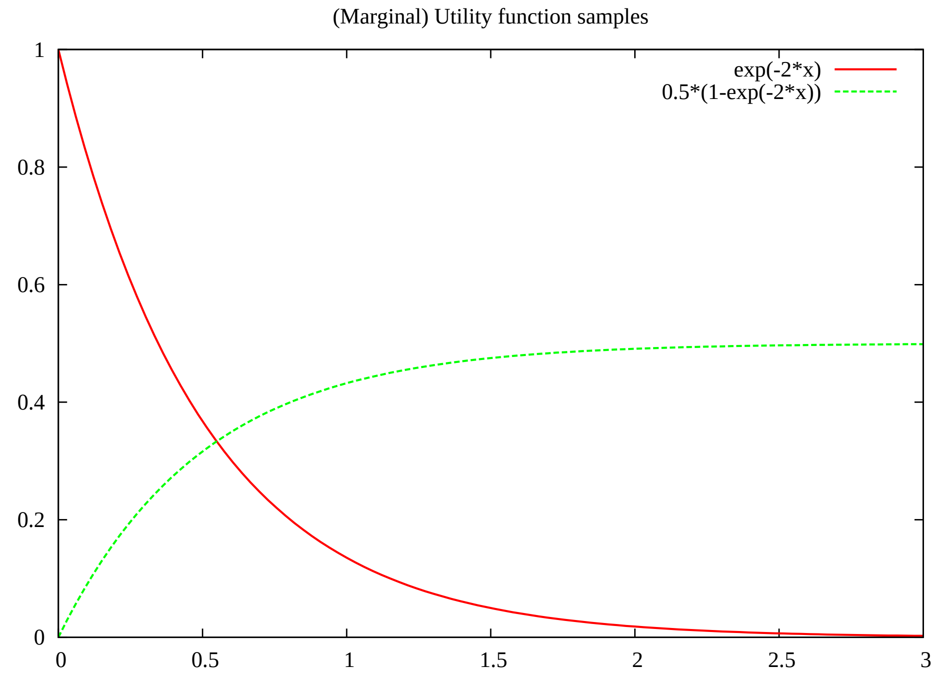

FIGURE 5 : Unit time utility function $v(d) = e^{-\alpha \cdot d}$ and its integral $\frac{1}{\alpha} \cdot (1 - e^{-\alpha \cdot})$ for $\alpha = 2$

2. Consider the largest subset of activities in an *optimal* schedule so that only the first (last) one starts (ends) at an externally stated time limit (e.g. shop closing time, time specified in public transportation timetable). Then, the marginal utility is the same for each activity period in that set since the utility is maximal.

3. Assume that activities a_i (predecessor in period $[t_{i-1}, t_i)$) and a_{i+1} (successor in period $[t_i, t_{i+1})$) can be performed as a sequence. The optimal moment in time t_i to start the successor is determined from

$$v_i(t_i - t_{i-1}) = v_{i+1}(t_{i+1} - t_i) \Leftrightarrow \qquad t_i = \frac{\alpha_i \cdot t_{i-1} + \alpha_{i+1} \cdot t_{i+1} + \ln \frac{k_i}{k_{i+1}}}{\alpha_i + \alpha_{i+1}} \tag{10}$$

Parameters determination from initial schedule

1. The k value used in the (marginal) utility function is assumed to be activity type specific. For the experiment k values have been chosen based on the idea that they represent the activity importance. However, they need to be estimated by a survey.

2. The α values are *time constants*: they are calculated from the assumed optimality criterion. For n_{act} activities, this condition leads to $n_{act} - 1$ equations. The n_{act}-th value is determined by assuming that, in each maximal subset constrained by time limits (as defined in section Utility Function item 2), the marginal utility for a reference activity dropped to a given fraction f of the original value for its duration $\overline{d}$ predicted by

Activity type	k.
HomeActivity	1.0
Work/school	2.0
Bring/Get	4.0
Daily Shopping	2.0
Non-daily Shopping	1.0
Services	2.0
	.

TABLE 1 : (Marginal) Utility k values for activity types used in simulation.

FEATHERS. Equation 12 shows that the reference activity reaches a fraction $1 - f$ of its maximal utility for duration $\overline{d}$. For our first experimental result, we arbitrarily chose the first activity in the schedule to be the reference activity with $f = 0.05$.

$$v(d) = k \cdot e^{-\alpha \cdot d} \Rightarrow v(\overline{d}) = f \cdot v(0) = f \cdot k \tag{11}$$

$$\Rightarrow \quad u(\overline{d}) = \frac{k}{\alpha}(1 - e^{-\alpha \cdot \overline{d}}) = \frac{k}{\alpha}(1 - f) \tag{12}$$

Since the k values depend on the activity type only, the specific (marginal) utility functions used, cause all activities of a given type enclosed between externally given time constraints in an optimal schedule, to reach the same utility. This however does not mean that they all have the same duration because the α values are activity specific.

3. It needs to be investigated how to determine the optimal choice of the reference activity by finding out whether the activity type or the duration is the relevant factor for selection.

Schedule Adaptation

1. After applying the disturbance to the network, affected informed and non-informed individuals get new values for the travel delay for one or more trips (each one at a specific moment in time t_0 defined by *notification* or *experience*). The amount of time to be spent to the (partial) activities and trips that have not yet been finished at time t_0 will change due to modified travel duration predicted from the network state.

2. For each individual (schedule) the new activity start times are calculated using a relaxation algorithm based on equation 10 that can be proven analytically to converge monotonically when a monotonically decreasing marginal utility is used.

SIMULATION RUN - NUMERICAL DATA AND RESULTS

1. For the first experiment, the k values given in Table 1 have been determined estimating the relative importance of activity types.

2. A simulation runs goes as follows:

   (a) FEATHERS is used to generate an initial schedule for every individual.

   (b) For each *NSE-period* p_0 the set of trips whose execution period overlaps with p_0 is determined. Each such set is used to assign traffic to the network using TransCAD. Travel times between TAZ are extracted from the TransCAD results. The set of affected individuals is determined as described in section Framework Conceptual Overview item 10.

   (c) For each newly affected schedule, the time at which the individual becomes aware is calculated: *notification event*.

   (d) As time evolves, at the end of every *NSE-period*, the new traffic state on the network is calculated and affected traveling persons who are not yet informed, become aware of congestion by experience: *experience event*. This event cancels an eventually pending notification event for the specific *(person,trip)* combination.

   (e) *Notification* and *experience* events for each person are processed in chronological order. The one that comes first, applies.

3. Total simulation time for 96 *NSE-periods* for about 2.9 million persons takes 19 hours computation time on a standard Intel i5 laptop running at 2.4 GHz and having 4 GB of memory. About 70% of the time is consumed by TransCAD for traffic assignment and shortest time paths calculations. The relaxation algorithm to find new optimal schedules when timing constraints changed, handles 21000 schedules per second.

4. First results include cumulative distribution functions (CDF) for (marginal) utility and travel time for the situations before and after rescheduling. They allow to compare time loss effects between *informed* and *non-informed* individuals.

FUTURE WORK

1. Bell-shaped marginal utility functions (leading to S-shaped utility functions) will be introduced. Joh (*3*) has shown that they provide a more realistic model of reality.

2. More elaborated models for the traffic information conveying model (broadcast, publish) need to be incorporated; the framework now is ready to do so. The sensitivity of the simulator to the notification model used, is to be investigated.

3. Activity dropping and insertion, activity re-sequencing, activity relocation all will lead to challenging combinatorial optimization problems. Cooperation between individuals will add another magnitude of complexity as is suggested by preliminar investigations in Knapen et al. (*11*).

CONCLUSION

A framework to investigate large scale effects of rescheduling daily activities has been built by combining microscopic simulation with macroscopic time dependent traffic network performance modeling. The microscopic component covers large amounts of agents re-optimising their daily agenda making use of network information via perception filtering as time evolves; this in turn influences the time dependent network load. Both the framework and a simple rescheduler using monotonically decreasing marginal utility have been evaluated and proved to be able to produce results for the complete flemish population and road network within a feasible runtime. The framework now is ready for evaluation of alternative (marginal) utility functions, traffic information conveying models and perception filters.

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