A Microsimulation Model for Assessing Urine Flows in Urban Wastewater Management

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Abstract: We report on a microsimulation model under development whose purpose it is to construct scenarios for the assessment of a novel wastewater management technology: the separate collection, transport, and handling of human urine. Levelling the urine flow to the treatment plant or removing it from conventional treatment altogether has many benefits for wastewater management. For an effective technology implementation, it is useful to know the spatial and temporal distribution of urine generation. This can be achieved with microsimulation modelling which depicts the objects under study on a one-to-one basis and thus allows capturing the co-variation of different variables across these microunits. In our case, microunits are buildings, apartments, toilets, and people; technology impacts are driven by physical characteristics of the building infrastructure and sociodemographic characteristics of people, including their mobility behavior. We are modelling a Swiss region comprised of 18 small municipalities that form the catchment area of a wastewater treatment plant. Swiss census data provides us with information on residential buildings and their approximate geographical location, apartments, and residents and their sociodemographic and employment profile. Using event-based simulation, we set up a daily agenda for every person in our model, sending them to work and on other trips and letting them urinate in different locations. In work to date, we could replicate the typical morning peak in urine generation and identify the areas with the greatest urine density. In future work, we will construct scenarios describing the diffusion of the technology. Diffusion can be modelled endogenously as we depict the behavior of microunits and can let them react to geographical and social information contagion. We find microsimulation advantageous because it captures the heterogenity of microunits, facilitates the linking of data from different sources, and allows many different questions to be addressed in one and the same flexible modelling framework.

***Keywords**:* Microsimulation; Scenario Analysis; Technology Assessment; Wastewater Management.

1. INTRODUCTION: THE APPLICATION

We report on a modelling effort whose ultimate purpose it is to assess the cost-effectiveness of a novel wastewater management technology. The model is still under construction, and more data is needed for a complete assessment. Yet part of the model already stands, and we can generate interesting results with practical applicability: the spatial and temporal pattern of urine flows in a model region. These flows matter for wastewater management technology decisions as they are being discussed in Switzerland and other European countries. In the following, we present the technology to be assessed; motivate our modeling strategy; describe the model, the data, and the software we are using; present first results and end with conclusions and an outlook on work to be done.

The technology to be assessed is the separate collection of human urine in a special “NoMix” toilet (Larsen and Gujer 1996, Larsen et al. 2001). Urine is stored in tanks located in building basements, transported through the sewer system at night when it is almost empty, diverted before it reaches the treatment plant, and guided to a separate treatment facility. Alternatively, the urine could be fetched by trucks.

The rationale for the separate handling of urine is its crucial role in urban wastewater management. Urine accounts for a large share of the nitrogen in residential wastewater, in terms of both overall quantity and temporal distribution. There is a characteristic daily nitrogen peak caused by people urinating after they get up in the morning; the size of this peak is the main factor driving treatment plant capacity (for plants yet to be built) or limiting the effectiveness of wastewater treatment (for plants that already exist). Also, urine contains residues of pharmaceuticals and natural hormones that are not completely eliminated during treatment; they are strongly suspected to contribute to the declining health of aquatic ecosystems.

Separate collection, transport, and treatment of human urine can be quite advantageous for wastewater management, reducing the need for chemicals and energy in treatment plant operation and improving the quality of plant effluent. Also, it could lessen the damage inflicted on surface water bodies by "combined sewer overflows" (releases of raw sewage during rain events). Last, not least, urine is rich in nutrients; provided it can be treated appropriately and harmful substances be eliminated, urine could substitute for synthetic industrial fertilizer and thus save phosphorus and other scarce natural resources, much better than sewage sludge which is so contaminated that it is about to be banned from agricultural applications in a number of countries. – Yet another advantage of urine source-separation is water conservation, as the urine toilet flush uses little or no water at all.

An intermediate version of the technology would store the urine temporarily and release it in controlled fashion to level the nitrogen peak arriving at the treatment plant. In that case, urine storage tanks built into the toilets would suffice. This technology version would be cheaper but still advantageous: Leveling the nitrogen peak still improves treatment (though not as much as removing urine from the wastewater), and the impacts of combined sewer overflows would still be lessened, if urine can be successfully withheld during rain events.

2. ASSESSMENT METHOD: SCENARIO ANALYSIS BASED ON MICRODATA

The impacts of the urine source-separation technology are driven by a number of factors. Improvements in wastewater treatment and reductions of environmental effects are the greater, the more urine is withheld temporarily to flatten the nitrogen peak, and/or the more urine is kept out of the treatment plant altogether. The costs of the new technology arise per toilet replaced, per tank installed in a building, and per litre of urine collected in an area served by a tributary sewer (which is the "density" of urine yield, so to speak). Furthermore, the timing of the technology implementation will matter greatly for its cost. Implementation will be cheaper when it happens in the course of independently occurring bathroom re-modelling or building renovations and new construction.

The cost-effectiveness of the technology (how much positive impact can be achieved per dollar expended) thus is not easily expressed by a single common denominator, but depends on the combination of different variables with different dimensions. An approach that suggests itself for assessing the interaction of these different variables is to construct scenarios that represent different possible states of the real-world system to be studied. In our case, this real-world system is a model region that reflects a typical pattern of housing infrastructure; the scenarios include a reference scenario representing business as usual, i.e. without the technology in place, and a number of scenarios representing different degrees of technology implementation, which are compared to the reference scenario.

There are two major strands of analysis to be carried out with such an approach:

- a "snapshot"-type analysis of the material flows resulting from a given level and pattern of technology implementation;
- the exploration of strategies for technology implementation: Where and when could the technology conceivably be installed; and what would these different installations cost?

Clearly, it would be desirable to capture the characteristics of our units of analysis – size and age of buildings and apartments, and number of people living therein – as they co-vary across microunits, i.e., across the individual study objects, rather than aggregates. Also, tracing microunits through time and allowing them to interact would facilitate the modeling of technology diffusion in the long run, and the spatial and temporal pattern of urine generation in the short run, as people move about, spend time at home, at work, etc..

Capturing the variation of characteristics of microunits is facilitated by the use of microdata, i.e. one-to-one representations of the units of study. If such data is not directly available, it can be constructed (or "imputed") from aggregate data distributions, as they are typically reported in census publications (see Clarke 1996b). We obtained Swiss census data that contains detail on individual buildings and persons, including their geographical location. We chose two model regions in Switzerland, one urban, one rural, that are typical of the densely populated, industrialized countries of West-Central Europe. The software we are using lets us simulate technology diffusion endogenously, rather than by exogenously assuming certain market penetration rates. This allows us to explore the effectiveness of policies, given assumptions about the reaction of actors to policy incentives.

The use of microdata places our exercize in the tradition of microsimulation models, which have long been applied for tax policy and urban transportation analysis (for recent discussions, see

Gupta and Kapur 2000, Harding 1996, and Wegener and Spiekermann 1996). Tracing objects individually through time would qualify our model as "dynamic microsimulation" (e.g., Harding 2000). We plan to do this for the building stock, if not for the human population in our model.

This paper reports on first results of the snapshot-analysis for the reference scenario of the rural model region: the catchment area of a wastewater treatment plant, comprising an area of some hundred square kilometres, and some 23,000 residents. The area lies within commuting distance to several larger cities (e.g., Basel), but is rural in character, for industrialized Europe's standards.

3. DATA AND SIMULATION TOOL

We obtained anonymized data from the Swiss Census of 1990 on residential buildings, apartments, and residents, and how they are linked to each other, down to a geographical detail of 100 m squares, or hectares, in the metric system. (We hope to get access to 2000 census data over the course of the next year.) The data contains information on the demographic characteristics of people which affects the amount of urine they generate (e.g., age), the time they spend outside their homes (employment status and weekly work hours) and which may influence their inclination to install a new technology (income, tenant or owner, education, etc.). Of residential buildings, we have size, owner type, use type, age, and year of last renovation. From auxiliary data sources, we have data on the location of work places. We use this data to replicate buildings and their geographical location and to simulate how people move between and stay at these different locations.

The software which lets us do this is VSEit, (pronounced as "use it"), the "Versatile Simulation Environment for the Internet" (Brassel 2001a, b). VSEit is a Java-based object-oriented simulation framework that supports efficient event-based simulation (see, e.g., Cassandras and Lafortune 1999). Events are scheduled for certain points in time during the period to be simulated and are placed in an event queue. They are processed one after the other, according to their place in the queue, regardless of how much real-world time is supposed to pass between the real-world events they are representing.

The reason we favor event-driven over time-driven simulation (which runs the model in small equi-distant time steps) is computing performance. In the snapshot analysis, several ten thousand people are each pursuing their own course of action over the day; in the long-run technology diffusion analysis, we have several thousand buildings whose individual histories we want to trace.

4. MODEL DESIGN DECISIONS

So far, we have worked out the detail and performed the largest part of the snapshot analysis for the reference scenario, simulating the spatial and temporal distribution of urine produced by the population of the rural model region during a day. The spatial distribution results from estimates about the amounts of urine produced per person and day (Rauch et al., 2002), adjusted by the person's age group; from the primary residence of persons, as indicated in the data; and from persons' simulated mobility behavior, which is partly based on our assumptions, partly indicated in the data. The temporal distribution results from assumptions about persons' daily time awake and data on urination patterns (the latter in Rauch et al., 2002).

We simulate a 24 hr day, differentiating between weekday, Saturday, and Sunday. These days differ in terms of the frequency with which people go to work, consult services, go for recreation and shopping, and so on. To correctly initialize the model, we actually simulate two days, the first of which serves to establish consistent behavior patterns for the model actors. After 24 hours, everyone is properly initialized; the day for which we report results begins at 6 a.m..

What matters for spatial and temporal urine generation is where, when, and how much people urinate. Regarding where people spend their time during the day, we distinguish between different groups with different mobility behaviors:

- small children who partly stay at home, partly attend daycare or kindergarten;
- students who attend school and university;
- full-time and part-time workers;
- people with no reported commercial work activity, including housewifes and -husbands, pensioners, and the unemployed.

For all of the above (except small children), we differentiate between four different age groups: 15 to 19, 20 to 39, 40 to 65, and over 65 years of age.

People spend time away from their home for the following purposes:

- going to work and lunch;
- going to school or university and for lunch;
- going shopping;
- using services (e.g., doctor's office, agency, restaurants);
- taking recreation trips (cinema, gym, etc.)

Any given person in the model is assigned a daily agenda describing whether, when, and for what amount of time she engages in any of the above activities. This agenda is partly based on the data, partly based on the probabilities we assign given a person's sociodemographic profile, plus some additional assumptions like shares of normal work times vs. shift work. At this stage, these probabilities and assumptions are largely our best guesses; we intend to consult auxiliary material later to refine them.

A person's daily agenda is planned in three steps. All points in time that events are scheduled for are drawn from probability distributions.

1. First, a skeleton of daily trips is planned. Given the person's employment status and weekly work hours, time at work and at lunch is planned; then, depending on time spent commuting (given in the data), the time they get up is planned; then recreation trips, then the time of going to bed and getting up the next day.
2. Depending on getting-up time, the person's first urination of the day is planned, then the other urinations subsequently. Here, we draw on data reported in Rauch et al. 2002, which we adjust for age, also allowing for a larger morning urination at the expense of the other urinations during the day.
3. Service trips (shopping, visiting doctor's office, renewing driver's license, etc.) are scheduled independently of the other stays a person has planned for the day.

Scheduling conflicts between events can occur in steps 2 and 3. They are resolved when they arise, through re-scheduling or unscheduling. For example, a person may want to urinate when no toilet is around; we assume he puts off urination until there is one. Another example is when urination is scheduled for a time that a person is already in bed at night. (Recall that going-to-bed time is scheduled before urination times.) In that case, the urination event is unscheduled. Finally, stays at services are set up to conflict with existing schedules; they receive priority over whatever other activity the person happens to be engaged in (work, recreation, etc.).

5. FIRST RESULTS

So far, we have simulated the mobility behavior of workers, and have not yet included their service trips except for lunch. All other persons in our model stay at home all day. As we have designed workers to be the population group with the most intricate mobility behavior (they stay at more locations than the other population groups), having tackled them makes it easy to model the other groups. Also, we do not yet have detail on non-residential buildings; therefore, we assume one virtual building for work, lunch, and recreation, respectively, as well as a virtual space for the commute (representing trains, train stations, etc.).

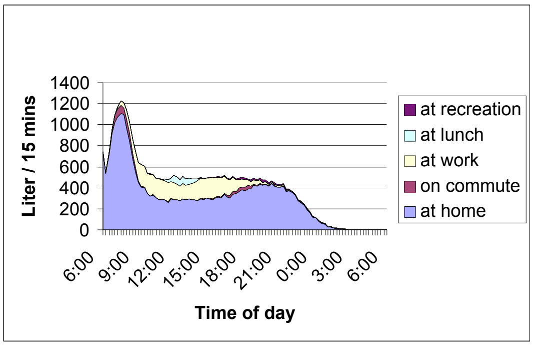

Figure 1. Temporal profile of simulated urine generation in rural model region on a weekday (litres per quarter hour). (Analysis based on data from the 1990 population census data provided by the Swiss Federal Office for Statistics.)

We collect model output in quarter-hour time steps. Figure 1 shows the temporal profile of urine generation arising in different types of activities, or stays: at home, during the commute to work (workers are assumed to be able to find a toilet on their commute provided it has a certain duration), at work, during work-related lunch, and at recreation. The residential contribution is rather large as all people except workers stay at home all day. We observe that given our assumptions about the distribution of people's work times and getting-up times, we replicate the typical morning urine peak. (Assessing when this peak arrives at the treatment plant would require including the time span that urine takes to travel in the sewer system, which we could estimate based on the location where it is generated and based on the layout of the sewer system; information we have access to for the largest part).

Figure 2 shows the spatial distribution of urine as it arises in the model region. The region consists of 18 municipalities that form the catchment area of a treatment plant (which lies at the Southeast of the area). One can easily make out urine clusters arising in the different municipalities.

Figure 3 shows individual hectares' contributions to total urine generation. We see that 4% of all hectares contribute 20% of the urine in the model area. Information such as this can indicate priority locations for technology implementation. Note that these figures only illustrate the type of analysis our model can perform. As long as we assume people stay at home all day, this information could be directly computed from the data, without undertaking simulations. However, as soon as we acknowledge that people move about, and that certain parts of a town may house a greater share of homemakers (who spend more time at home), simulation with microdata can yield additional interesting insights.

Figure 2. Spatial profile of simulated urine generation in rural model area on a weekday. Dots represent hectares (100 x 100 m squares); darker shading indicates a higher urine volume. (Analysis based on data from the 1990 population census provided by the Swiss Federal Office for Statistics.)

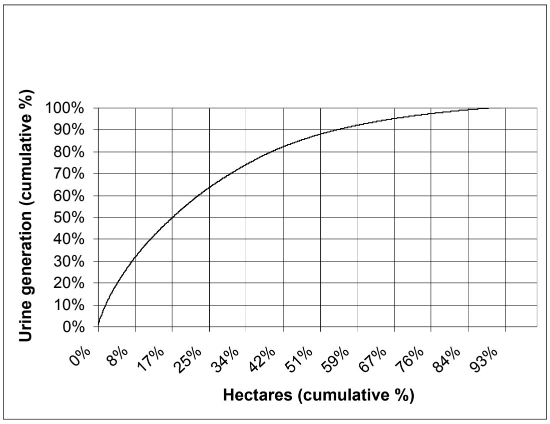

Figure 3. Cumulative contribution of hectares to total urine generation in model area. (Analysis based on data from the 1990 population census provided by the Swiss Federal Office for Statistics.)

6. WORK YET TO BE DONE

Clearly, a lot of work remains yet to be done for an assessment of the cost-effectiveness of technology implementation strategies. Work to be done for the snapshot analysis includes extending the simulation of mobility behavior to all groups of people. Then, microdata on non-residential buildings need to be constructed. We already have microdata on work places and their location, plus mesodata on non-residential buildings (types of buildings according to size and use type in different municipalities). Water consumption from toilet flushing is already set up for residential buildings but not reported here. Also, we will receive estimates for the cost of installing different elements of the NoMix technology: toilets, tanks, control devices, and so on, which will have to be incorporated into the model.

Work to be done for the long-run analysis mainly consists of constructing credible scenarios of the development of the housing stock. We have already run test simulations for future renovations of existing buildings but need to complete this analysis by new construction and demolitions.

The most interesting task will be to model technology diffusion. Here, we could for example formulate technology implementation strategies of the public sector exogenously (e.g., having the public sector install the new technology in certain public buildings, like hospitals and schools) and then complement these with diffusion based on the geographical or social proximity of building and apartment owners to new technology installations. (By social proximity, we mean that persons are exposed to NoMix technology during their daily activities, for example, at the doctor's office, at school, at work, etc.). Also, we could model the effect of policies that provide incentives for installing the new technology, including water pricing, technology subsidies, or leying wastewater fees on its nitrogen content (a policy that would raise the issue of monitoring).

7. CONCLUSIONS

The model described herein may sound rather complicated, especially for those researchers that work with equation-based models describing the behavior of system components at some level of aggregation. To be sure, specifying microbehavior is a cumbersome task. Yet the microsimulation approach yields many advantages. It allows the linking of data from different datasets, as long as they contain some overlapping information. (For example, in our case, we can link data from the population census with data from the work place census, via the geographical coordinates for persons and workplaces.)

Microsimulation allows many different questions to be addressed in one and the same framework. Any one question may be analyzed with much less effort using a simpler approach. (For example, Rauch et al., 2002, use a stochastic analysis where we use microsimulation, to obtain the temporal the profile of nitrogen load arriving at the treatment plant.) However, the strength of a modelling effort like ours lies in its flexibility. It provides a "virtual world" in which experiments of all sorts can be carried out. It can be expanded to address questions that were not on the horizon when the model was conceived and construction began (for example, simulating the behavior of urine in the sewer system, provided that information about the layout of the sewer is added to the model, which in principle is possible).

A critical issue is model validation. Clearly, we are pleased if we can replicate generally observable macropatterns, like the temporal profile of total urine generation. Typically, though, a given macropattern can be produced by many different micropatterns, and often one cannot be sure whether the assumptions about microbehaviors that generate the macropattern are correct, even if statistical analysis is used to identify the parameters of macro-relationships. This problem plagues many modelling efforts (esp. economic models rooted in the neoclassical microeconomic tradition; see Stoker 1993, and Orcutt et al. 1961).

This issue becomes crucially important when "structure breaks" are occurring, i.e., changes in the relationships between the real-world counterparts of model components. Models that provide reasonably good prognoses of aggregate relationships (e.g., macro-econometric business cycle models) might suffice as long as micropatterns are stable. As soon as micropatterns change (e.g., the determinants of consumers' purchasing behavior), these models tend to fail. Microsimulation, if based on careful representation of microbehaviors, offers at least the chance to understand, replicate, or even anticipate structure breaks. In our context, it lets us explore, in a consistent fashion, the effects of changing settlement patterns, household structure, and mobility behavior.

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