Using Time-Use Surveys in Multi Agent based Simulations of Human Activity

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Abstract: Human behavior simulations in multi agent systems often lack data to calibrate and qualify the representativeness of the simulated behaviors. In this paper, we will show that massive investigations such as time-use surveys allow us to obtain this type of data. At the present time, time-use surveys are mostly used to validate the realism of human activity at a macroscopic level (population scale). In this paper, we present a new method of human behavior generation that combines the use of time-use surveys to calibrate human activities, with a multi agent system enabling simulated behaviors to gain reactivity, autonomy, coordination and realism at a microscopic level (individual scale).

1 INTRODUCTION

During the last decades, computer simulations have become indispensable tools in many research areas such as energy, meteorology, geography, etc. (Law et al., 1991). Yet, how one can calibrate models and validate the realism of the produced activities remains an open question (Rakha et al., 1996; Caillou and Gil-Quijano 2012; Lacroix et al., 2013).

This is particularly true within the context of human activities simulation, where one can find an abundance of simulators focusing on different aspects, such as facial expression realism (Pelachaud, 2009), crowd movement (Thalmann et al., 2007) or the decisional process (Laird, 2012). Each of these domains needs the development of adapted validation methods.

Our research framework is human activity simulation in order to study residential electricity consumption (Amouroux et al., 2013). Many studies deal with this type of human activity simulation in the world of multi agent systems (MAS). Depending on the simulation's needs, the simulated human activities can either be highly scripted (Ulicny and Thalmann, 2001; Sharma and Otunba, 2012) or result from the behavior of more autonomous agents (Rao and Georgeff, 1991; Traum et al., 2003; Shendarkar et al., 2008). Other approaches try to combine the advantages of both previous methods (Grosz and Kraus, 1996; Tambe, 1997; Hubner and Sichman, 2007; Lanquepin et al., 2013).

In all these approaches, the issue arises: how to validate the realism of the produced activities? As many authors have shown, for example in (Gratch et al., 2009; Darty et al., 2014), the notion of "realism" can be viewed from several angles, depending on the type of simulation: likelihood or frequency of individual behavior consistent with each other over time allowing to reproduce high-level indicators, loyalty to the psychological level of decision making, etc.

One way of measuring the realism of a human behavior simulation, is to confront individuals with their own activity simulation, following a participatory simulation approach (Drogoul et al., 2003; Haradji et al., 2012). However, this method drastically lacks scalability. The amount of time needed for the interviews and the case by case basis of activity modelling make it impossible to simulate a large number of individuals and measure the realism of the simulation.

Is it possible to automate this process? In order to do so, one needs data about the activities of a large number of individuals, formatted in a model allowing to objectively compare them. Yet, this data exists in the time-use surveys (TUS)(Stinson, 1999). TUS are daily surveys in which respondents must transcribe

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their day as a series of episodes. These surveys exist in many countries and are well standardized. Statistical methods in the field of energy simulation use these TUS in order to simulate human activity and calibrate their models at a macroscopic level. The realism of the activity produced is then measured in terms of statistical proximity with the actual observed behavior. In this article, we propose to use TUS to produce realistic behavior following this statistical definition.

We will first present some methods of human behavior simulation in the field of multi agent systems, as well as statistical methods using TUS in the world of energy simulation. We will show how ensuring the realism of behavior at a macroscopic level is not enough to ensure the validity of individual behavior. Moreover, we will argue that combining the use of TUS with agent-based modelling improves the realism of the simulated individual behaviors. We will continue by giving more details about our method of human behavior generation, combining a MAS model and a TUS-based model.

2 STATE OF THE ART: HUMAN BEHAVIOR SIMULATION

2.1 In Multi Agent Systems

In the field of human behavior simulation, the multi agent approach offers several modelling methods. The choice between these methods depends on the goals of the simulation.

Scripted behaviors planned in advance by the modeller can be used, for example, when the expected behaviors are well known and sufficiently well formatted. Those are typically used in training simulations where the purpose is to expose a learner to a specific scenario (Sharma and Otunba, 2012), or in the case of urban emergency situations (Ulicny and Thalmann, 2001).

In such approaches, one tends to limit the behavior autonomy in order to ensure that the simulations will be conducted as desired. Conversely, it may be useful to model much more autonomous behaviors, for example within the context of negotiation and team work (Traum et al., 2003). One way to do so is the BDI model (Belief-Desire-Intention) (Rao and Georgeff, 1991), widely used in multi agent based simulations (MABS). In this model, the agent's goals and belief are modelled. Thus, its behavior is a means used in order to achieve its goals. These models are also particularly interesting in large-scale simulations (Shendarkar et al., 2008), since scripts are difficult to implement in highly unpredictable and unstable environments.

On a wider angle, when one tries to model collective behavior, it becomes necessary to use prescribed coordination models (Lanquepin et al., 2013), and to combine them with reasoning mechanisms. Several ways to achieve that combination exist. For example, (Hubner and Sichman, 2007) proposes to build a system of organizational constraints that each agent must respect. Rather than constrain the behavior of autonomous agents, one may seek to equip agents with teamwork models to enable them to coordinate themselves in an adaptive and flexible way (Tambe, 1997), or allow them to collectively plan their actions (Grosz and Kraus, 1996).

Our work follows a combined approach with both prescribed activity at a global scale and autonomous decision making for action selection at a fine-grain level.

2.2 Statistical Methods using Time-Use Surveys

TUS are daily surveys in which respondents must transcribe their day as a series of episodes. For example in the French TUS used in our research (INSEE 2010), respondents had to indicate which activity they were currently doing, every 10 minutes for the whole day.

The use of TUS in simulations is restricted to a few applications only, including the simulation of household energy consumption. These are not as widely used as they could be, certainly due to the lack of visibility of these studies outside the world of statistics. Moreover, if TUS are so attractive in the world of energy, it is because it has been shown that modelling residential energy consumption cannot be realistic without any consideration about human activity (Hitchcock, 1993). To improve the realism of simulated consumption load curves, it is necessary to integrate statistically realistic human behavior models.

It is possible to distinguish two main trends in the use of TUS to simulate human activity: "top-down" approaches and "bottom-up" ones.

2.2.1 "Top-down" Approaches

The TUS data can be used to compute a matrix which determines, at every time of the day, the probability for an individual to switch from an activity to another. (Richardson et al., 2010; Widén et al., 2012) use

Markov chains to model these probabilities for a change in activity (a simple presence / absence in the housing in the first case, and ten classical activities in the second). Similarly, (Chiou, 2009) uses a bootstrap method (DeGroot, 1986) to extract the structure of the daily behavior in US households.

These approaches are traditionally limited by three factors (Yamaguchi and Shimoda, 2015). First, they need to have the raw data of the TUS, but this data isn't always freely available, depending on the laws of the country. Second, they lack accuracy about the duration of the different activities. Because these approaches focus on transitions between activities, the length of each one may be less strictly simulated. Finally, the coordination between members of the same household is difficult to consider. Indeed, the matrix of activity switches is not intended to be dependent on the environment (or other agents).

2.2.2 "Bottom-up" Approaches

The TUS data can also be used to determine the mean duration and distribution of activities during the day. With this information, the "bottom-up" approaches are able to build schedules iteratively, selecting activities one after the other, according to a probabilistic distribution. When the new activity is selected, the duration is also calculated with the same method. Thus, with each new selection of behavior, it is possible to take the current situation into account.

(Tanimoto et al., 2008) show that this approach does not require us to have access to the raw data of the surveys. The only information needed is:

- the mean duration (and the associated standard deviations) of each activity
- the percentage of individuals who adopt a specific activity at a given time (this percentage is called PB)

The timetables are built iteratively from an initial activity by randomly choosing the next activity from PB, when the previous activity ends.

(Wilke et al., 2013) improve the method by initially taking into account the periods of presence / absence of individuals in their housing. From the perspective of the simulation of energy consumption, the presence or absence of any individual in the habitat fundamentally alters the housing consumption profile. Therefore, it seems appropriate to use it as a "framework". When a person enters the house, the model determines the first activity to be selected as well as its duration, and so on until he leaves. Then the model directly "jumps" to the next attendance period.

Another method, developed by (Yamaguchi and Shimoda, 2015) also uses a strict structure of activities, but through behaviors called "routine". Thus, activities such as sleep, work and study, along with those related to meals and hygiene are initially placed in the timetable. Other behaviors are then selected in order to fill gaps in the schedule. The originality of the method is to give prior attention to activities structuring the schedule. Through these routine activities, it is possible to take into account an early coordination between members of the same household.

All these statistical methods (top-down and bottom-up) aim to replicate realistic human activities at a macroscopic level. The simulated activities are intended to match with the observed ones only at a macroscopic scale. However, this approach does not focus on the simulation of realistic individual behavior. There is indeed no need to simulate a collection of individually realistic behaviors to simulate a realistic aggregate behaviour (Thalmann et al., 2007). In a way, the simulated individual behaviors are not taken into account, but they are only "emerging" from the targeted aggregated behaviors. This is the reason why we are going to combine the high-level TUS-based approach with the MABS.

2.3 The Interest of Coupling MAS and Statistical Methods

One goal of simulation in energy consumption is to provide predictions of the future evolution of load curves as new practices appear in the household (*e.g.* new electronic devices or low-consumption appliances), or the projection in fictional situations (*e.g.* to assess the impact on the load curve of a major event such as a sport competition or weather change). Understanding such evolutions requires to generate individually realistic behavior over time, able to respond and adapt to environmental changes. However, statistical methods offer limited information on this regard.

2.3.1 The Limits of Statistical Methods

Statistical methods are not trying to simulate autonomous or even reactive individuals. Statistical methods aim at reproducing observed behavior in a reference situation (the situation corresponding to the TUS). They cannot be applied to unknown situations, in which there is no statistical data to match. Statistical approaches also do not aim at generating individually realistic behavior over time, able to respond and adapt to environmental changes.

Similarly, none of the above statistical methods completely deal with the issue of agents' coordination, since it is not essential to ensure the realism of the activities at a macroscopic level. In the best case, a limited coordination is restricted to a few "routine" behaviors (eat, wash, etc.). However, many other behaviors require coordination (from a family walk to helping a child to get dressed, or even choosing the set temperature for the housing). That is why, in order to simulate energy consumption as well as other applications, having a coordination model between simulated individuals is a necessity.

2.3.2 The Benefits of the Agent Centred Approach

Unlike statistical methods, the agent centred approaches use models centred on the simulated individuals. Therefore, they aim for a validity at the individual level. In MABS, the "emerging behaviors" are the collective ones, as they are not explicitly described in the model, but arise from interactions between individual agents (Drogoul and Ferber, 1992).

In our work, we are interested in realism at a macroscopic level (population scale) and we need the TUS data to calibrate the simulated activities. However, we are also interested in validity at a microscopic level (individual scale) for prediction and simulation of fictional situations. We want to be able to simulate reactive, autonomous and cooperative behaviors over time. That is why we developed another method that combines the advantages of both statistical and agent-based approaches. Our method is in this sense a "mixed" MAS method, using reactive and autonomous agents, whose behavior is calibrated from statistical models derived from TUS.

3 OUR PROPOSITION

3.1 General Principle

This section presents our model of human behavior generation. It is based on the combination of a bottom-up approach to TUS with an existing and already validated agent model: **SMACH**. We will first present our agent model, then the TUS we applied to calibrate the model. Afterwards, we will discuss two specific issues encountered. First, which data to collect in the TUS in order to increase the validity of the simulated activities at a microscopic scale. Second, how to generate both routine activities and activity variability over time. We will then give more details about the activity generation algorithm, and two possible methodologies in order to validate the model.

3.2 Description of the SMACH Agent Model

SMACH is a simulation platform of human activity inside the housings. Its ability to simulate individual behaviors similar to real ones has already been validated (Amouroux et al., 2014). In this platform, each individual is modelled as an agent with goals (tasks to perform), knowledge (about the other individuals and the environment) and preferences (either in terms of comfort or behavior). The agents are able to exchange information, coordinate with each other to perform specific tasks, plan their days (agents can have preferences about when to perform a specific task) and their weeks (for example, agents can have preferences about the number of times per week they wish to use a washing machine).

All the information needed to launch a simulation are called the "scenario". It contains a description of the housing (type, surface, insulation, etc.), weather conditions, household type and individuals. In a scenario, each individual has a set of tasks to perform. These tasks have the following features:

- **Duration.** Each task has a minimum and a maximum duration. When an agent performs a task, its priority increases compared to the other ones, in order to prevent constant activity swapping. The priority of this task decreases after reaching the minimum duration, and it is reduced to its minimum value after reaching the maximum duration.
- **Rhythm.** Each task can be assigned a number of repetitions per day or per week. For example: the task "sleep" takes place once a day, the task "use the washing machine" takes place three times a week.
- **Preferential period (PP).** Each task may be associated with a PP indicating the periods during the day (or the week) that are preferred for carrying out the task. These periods may be more or less strict, that is to say that agents may or may not be allowed to achieve the task outside the PP. The PP changes the priority of the task, positively during the period, and negatively outside.
- **Community.** This indicates whether this task is rather accomplished alone or in groups. Example: "having meals" is rather a collective task while "brushing teeth" is rather an individual one. The realization by an agent B of

a collective task also achievable by an agent *A*, gives a bonus to the task's priority for the agent *A*.

- **Location.** Each task is associated with a location, inside or outside the housing.

These features illustrate an important advantage of using an agent centred model. It becomes unnecessary to generate a scripted schedule minute per minute. Preferential periods are sufficient for autonomous agents to determine themselves the sequencing of their tasks from a list. In addition, the agents themselves manage their coordination through internal models (in this case, the community feature).

3.3 The TUS Used

Our proposal is to use TUS data to set the parameters of the MAS simulation (task information for each individuals of the household). While our method is generic from the perspective of the TUS used (the data of any TUS can be used because they all follow a common methodology), in was applied to a specific TUS: the French 2009-2010 "*enquête emploi du temps*".

3.3.1 Description

This TUS was conducted by the INSEE institute in 2009-2010 (INSEE 2010). It interrogated 12,000 households, in which one or two people per household filled one or two timetables. A timetable consists of 144 time slots of 10 minutes each, from 21:00 until 23:50 the day after. For each time slot, the respondent must indicate what activity he is currently performing. In this TUS, more than 18,500 people filled around 27,000 timetables. There are 140 activities identified in the survey.

This subdivision is too precise for the goals of our simulation. Indeed, dealing with very precise activities have two negative consequences. First, it unnecessarily increases the complexity of the model: the activities "reading" and "reading a newspaper" of the TUS can be simply modelled as a single activity "reading" in the simulation. Second, the more different activities are in the survey, the less repetitions each of them receives. That leads to under-represented activities in the survey, and therefore insignificant ones (for example activities like "going on strike" or "receive medical care from a professional at home" are not observed enough in the survey to be significant).

So, we operate a transformation to change the 140 activities in the TUS to only 30 activities in our model (more consistent with our simulation's goals), such as: "to sleep"; "to work"; "hygiene"; "to watch TV"; "to wash the laundry"; "to wash the dishes"; "to cook lunch", etc.

Please note that this transformation of activities from the survey is optional, and depends on the simulation's goals. In this case, we are interested in household electrical consumption, so the activities are mainly inside the housing, and energy driven.

3.3.2 Individual Types

In a similar manner as the statistical methods presented in the state of the art, we do not try to characterize the behavior of individuals in general. We define a typology of individuals, which allows us to categorize the timetables based on the individual characteristics of the person who completed them. The more we have access to specific individual characteristics, the more we are able to identify a typology of specific individuals, and the more the schedule will be representative of those types. However, the fewer timetables associated with a type of individual, the less representative the schedules are. The goal is therefore to build the most discriminating individual typology possible, while avoiding under-represented types. We decided to retain the following individual criteria:

- Sex
- Age
- Professional activity (student, working person, unemployed, pensioner)

There are no timetables filled by children under 10 years. So we decided to build categories with 10 years age range, starting from 10 years old (up to 60), and a last category for those over 60 years. Since all combinations of these three criteria (sex, age, activity) are not possible (no woman under 20 years old is a pensioner, for example), we get 27 different types. The smallest group has around 170 timetables, while the biggest has over 4,000 ones.

Please note that the TUS data do not allow us to model children under 10 years old.

3.3.3 Type of Day

Another consideration needs to be taken into account: the type of day. Indeed, for the same individual, the activities carried out on weekdays and on Sundays are rarely similar. But the type of day is also dependent on the individual's type. The usual Monday activities from a working person and from a pensioner could be highly heterogeneous. We use the following typology:

- “working day” or “weekday” (“working day” for active and students, and “weekday” for unemployed and pensioners)
- rest day

Please note that, during the survey, timetables filling days have been deliberately divided equally between weekdays and weekend. So, we have an almost equal distribution for each type of individual, between rest days and working day (51.4% of weekdays).

Please also note that this segmentation of individuals and types of day depends on the simulation’s goals.

3.4 Data Collected from TUS

3.4.1 Comparison between Statistical Macroscopic Results and Individual Schedules

By studying the TUS’s timetables individually, it appears that the statistical results at a macroscopic level do not give much information about behaviors at an individual level. A simple example: the "sleep" activity (see figure 1).

These curves show the percentage of individuals of the four categories "working person", "student", "unemployed" and "pensioners" performing the "sleep" activity during each step of the day. From these curves, one can easily draw firm statistical conclusions such as "on average, students get up later than pensioners, who are those who go to bed the earliest”. These results are very interesting and fairly simple to reproduce statistically.

However, these results conceal a substantial part of the individual behavior variability. Even if an average of 95% of the pensioners is sleeping between 2 AM and 4 AM, it is not necessarily the same 95% at 2 AM and 4 AM. The study of individual timetables shows that activities interruptions are very common. Thus, in 10% of the timetables, the sleeping activity was reported several times during the day (and up to 7 times), or no time at all. This example illustrates the gap between aggregated and individual behavior. Modelling the human sleeping activity as an activity carried out only once per night for a duration of 8 hours may be enough to match the behavior distribution at a macroscopic level. But this does not model individual realistic sleeping behaviors in the sense that in many cases, the simulated behaviors may not match the actual observed ones because of their number of repetitions per day, or their mean duration (people wake up during the night, sleep several times a day, etc.).

Yet the sleeping activity is really easy to model: it is an activity adopted every day by almost everyone, with a simple schedule. For an activity much more difficult to model such as "being on the phone", one can easily imagine the difference there may be between the aggregate and individual behaviors.

3.4.2 Enhance the Information Extracted from the TUS

The information typically used by statistical methods are the mean durations (and the associated standard deviations) of each activity, as well as the percentage of individuals who adopt a specific activity at any given time. This data is sufficient to generate realistic activities at a macroscopic level, but lacks realism at a microscopic level, because it does not take into account the number of times each activity is actually repeated each day. That is why we extract more information from the TUS, in order to match more precise activity features at a macroscopic level.

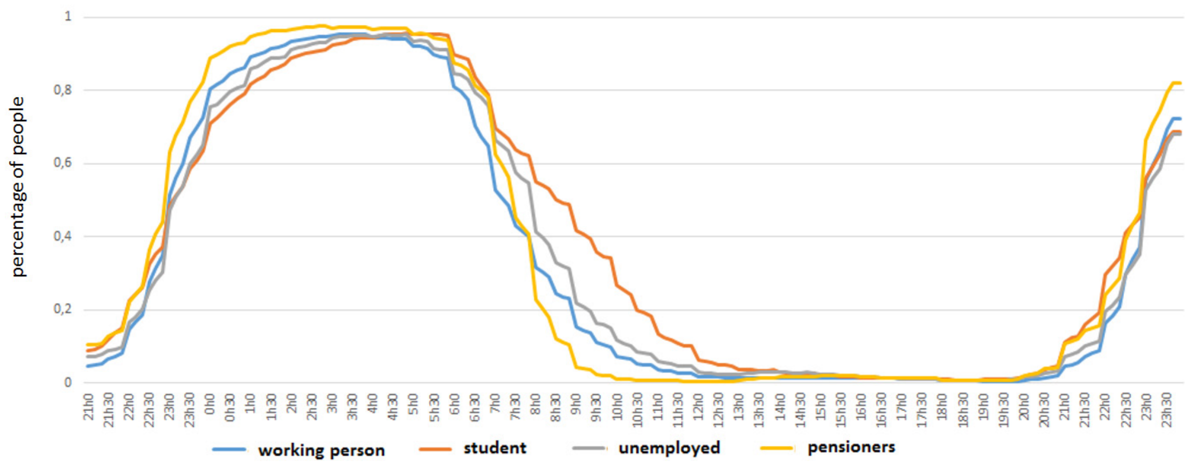

Figure 1: The "sleep activity" over time.

Let $N(a, t)$ be the number of repetitions of the activity a, in the timetable t.

Let $P_N(a, i, d)$ be the probability distribution of $N(a, t)$ for the activity a, for all individuals of type i and for all days of type d.

For each P_N, let $D_{P(N)}$ be the collection of couples (starting time, finishing time), from every episode of the activity in P_N.

Our model requires to extract from the TUS all $P_N(a, i, d)$ and all $D_{P(N)}$ for every activity a, every individual type i, and every type of day d.

Please note that the usual data used by statistical methods (mean duration/standard deviation and percentage of individuals adopting a specific activity at a given time step) are included in this data.

If this new information is taken into account during the process of macroscopic matching between observed activities and simulated ones, we believe that the simulated individual activities are much closer to the observed ones, and thus more realistic. That is why we will build in our agent model the parameters for task description based on this information. However we must also deal with activity variability over time.

3.5 Activity Variability over Time

3.5.1 The Absence of Information on the Variability of Activity in the TUS

Another difficulty is the absence in the TUS of information about the variability of activity over time. For the same individual, no more than two days of their life are given, and these days are never consecutive (usually a weekday and weekend day). From one or two timetables of an individual, it is impossible to know if the times, durations and frequencies indicated for each activities are rather usual or exceptional.

Example: Let T_1 and T_2 be two timetables collected in the TUS (respectively a Wednesday and a Saturday) for an individual *A*. In T_1, only 4 hours of sleep are indicated, and 10 hours in T_2. What does it say about the average sleep durations of *A*? It is impossible to know if these values are representative of the mean duration of sleep on weekdays and weekend or not. *A* could be sleeping 4 hours per night during week nights, or this Wednesday he might have attended a party and slept less than usual.

This problem does not appear when one attempts to generate a schedule for only one day, because in this case, it doesn't matter if the activities observed in the TUS are usual or not; one just has to reproduce them. But when one wants to generate a schedule for weeks or months, one needs to know if the activities are usual or not, because only the usual activities should be repeated day after day.

In order to generate individual realistic human activity over time, one has to generate routine activities which will regularly be the same, but also variations around these routines (Feldman and Pentland 2003; Haradji et al. 2012).

This means that generating the schedule for a week with copies of the same day over and over is impossible (no activity variability). On the other hand, generating the schedule for a week with totally different days each day does not bring more consistency over time (no routine activity).

3.5.2 Weekly "Routine" Schedule

Our proposal to solve this problem is to generate the information that is lacking. To do so, we will make one strong hypothesis by considering that the most atypical behaviors at a macroscopic level (the least represented ones in the TUS) are also atypical ones at a microscopic level, that is to say that they are only special cases, specific exceptions, and cannot be the routine behaviors of any individual. That is a simplify model of the reality. It is possible that some humans exhibit routine behaviors that are atypical: for example, some humans do sleep on average 2 hours per night. But since these cases are very uncommon, we do not take them into account.

Weekly "routine" schedules will be based only on regular behaviors. All the other behaviors (unusual ones) found in the TUS will allow us to feed the variability around routine behaviors.

For each simulated individual we will create a weekly routine schedule based on all regular behaviors on the timetables corresponding to his type. The unusual behaviors of these timetables will indicate how the behavior of the agent will change around that routine.

In this way, the mean duration and standard deviation of each activity are kept realistic at a macroscopic scale, but the individual behavior gains consistency over time.

3.6 Details of the Algorithm

We will now present the algorithm we use to generate schedules. Please note that this algorithm is generic to the extent that it works regardless of the typology of individuals, the days and activities or the TUS plugged in. The individual timetables are not required as long as the data presented in the section 3.4.2 are available.

Table 1: Table presenting all notations of the algorithm.

$N(a,t)$	number of repetitions of the activity *a*, in the timetable *t*
$P_N(a,i,d)$	probabilistic distribution of *N(a,t)* for all individuals of type *i* and for all days of type *d*
$D_{P(N)}$	all couples (starting time, finishing time), from every episode in $P_N(a,i,d)$
$mean(D_{P(N)})$	mean duration of the episodes from $D_{P(N)}$
$stddev(D_{P(N)})$	standard deviation of the episodes from $D_{P(N)}$
$PP(D_{P(N)})$	preferential period of the activity in $D_{P(N)}$
DRS(ind,d)	daily routine schedule of the simulated individual *ind*, for the days of type *d*
WRS(ind)	weekly routine schedule of the simulated individual *ind*
DS(ind,rd)	actual daily schedules for the individual *ind*, for the real day *rd*

3.6.1 Step 1: Calculation of Temporality Information

Let *A* be the set of activities of the simulation
Let *I* be the set of individual types
Let *D* be the set of types of day
For every activity *a* in *A*, for every type of individual *i* in *I*, and for every type of day *d* in *D*, we first compute $P_N(a,i,d)$ and $D_{P(N)}$ (see section 3.4.2 for definitions).
For every $D_{P(N)}$, we compute $mean(D_{P(N)})$ and $stddev(D_{P(N)})$, the mean duration and standard deviation of episodes from $D_{P(N)}$.
We then build $PP(D_{P(N)})$, the preferential period of the activity. The *PP* are calculated such as 75% of the episodes from $D_{P(N)}$ start after the starting time of *PP*, and 75% of the episodes from $D_{P(N)}$ finish before the finishing time of *PP*.

3.6.2 Step 2: Determination of Daily Routine Schedule

Let *DRS(ind,d)={task*$_1$*, task*$_2$*, …, task*$_m$*}* be the daily routine schedule of the simulated individual *ind* (which individual type is *i*), for the type of day *d*. This schedule is a collection of tasks (see section 3.2 for a definition of task in the model)
For every activity *a* in *A*, let *x(a)* be a possible number of repetition of *a*, chosen randomly in $P_N(a,i,d)$. We then create a task *ta*, corresponding to the activity *a*, with the following properties:

- Minimum duration = *mean*($D_{P(N)}$) - *stddev*($D_{P(N)}$)
- Maximum duration = m*ean*($D_{P(N)}$) + *stddev*($D_{P(N)}$)
- Preferential period: *PP*($D_{P(N)}$)

We add *x(a)* repetitions of the task *ta* in *DRS(ind,d)*

3.6.3 Step 3: Determination of Weekly Routine Schedule

Let *rd* be any real day of the week (Monday, Tuesday… Sunday).
Let *WRS(ind)={DRS(ind,d*$_1$*) , … , DRS(ind,d*$_k$*) ,… , DRS(ind,d*$_n$*)}* be the weekly routine schedule of the simulated individual *ind* (which individual type is *i*), with d_1, …, d_k, … d_n the *n* different type of day in *D*.
For every type of individual *i* in *I*, let *Pdj(i,rd)*, (with *j*ϵ*[0,n]*) be the probabilities that the day *rd* be of type d_j for an individual of type *i*.
For every day of the week, we add in *WRS(ind)* the corresponding *DRS(ind,d)* thanks to a random draw in *Pdj(i, rd),* (with *j*ϵ*[0,n]*).

3.6.4 Step 4: Determination of the Simulated Schedules

Let *ind* be a simulated individual.
Let *DS(ind,rd)={task*$_1$*, … task*$_m$*}* be the actual daily schedules for the individual *ind*, for the real day *rd*.
DS(ind,rd) is build as follows:
for every type of day *d*, we determine the daily routine schedules *DRS(ind,d)* (step 2) and the weekly routine schedule *WRS(ind)* (step 3).
Then, for every new simulated day *sd* (which type of day is *d*), for every task *ta* in *DRS(ind,d)*, we add *ta'*, a copy of *ta*, in *DS(ind,rd)*. But there is a probability of 0.3 that we turn *ta'* into an "unusual task" (see section 3.5.2). This corresponds to the fact that, statistically, only 68.2% of the episodes have a duration situated in the interval [mean($D_{P(N)}$) - stddev($D_{P(N)}$) ; mean($D_{P(N)}$) + stddev($D_{P(N)}$)].
However, at this point of the algorithm, every episode is inside this interval. So, in order to keep a realistic variability of these durations at a macroscopic level, we have to "push" 1/3 of these durations outside the interval.
Turing *ta*' into an "unusual" task is done by the following operation:
With a probability 0.3 (probability of unusual task), select randomly one of the two possible alterations (this choice is equiprobable):

a) Set minimum duration = mean($D_{P(N)}$) - 2*stddev($D_{P(N)}$)

Set maximum duration = mean($D_{P(N)}$) - stddev($D_{P(N)}$)

b) Set minimum duration = mean($D_{P(N)}$) + stddev($D_{P(N)}$)
Set maximum duration = mean($D_{P(N)}$) + 2*stddev($D_{P(N)}$)

Please note that, statistically, around 4.5% of the durations are outside the interval [mean($D_{P(N)}$)-2*stddev($D_{P(N)}$);mean($D_{P(N)}$)+2*stddev($D_{P(N)}$)]. We do not deal with them (we consider those tasks as too rare).

3.6.5 Conclusion about the Algorithm

With this algorithm, the duration and standard deviation of the simulated activities at a macroscopic level are still respected, but the average number of repetitions of each activity is respected too. In addition, the simulated individuals exhibit both routine activities and variation around them. We believe that these features increase realism in the individual schedules generated.

In this algorithm, we suppose that the tasks are independent from each other, but it is possible to deal with such dependencies during the random draw in P_N during step 2 (for example to take into account that if an individual is cooking during the day, he is more likely to eat at some point after that).

The tasks created by this algorithm are not complete at this point. They lack community and location information. This information cannot be found in the TUS, it has to be added by the modeller. So, for each activity of the simulation, the modeller has to explicitly fill up the features “community” and “location” (see section 3.2).

With this additional information, the tasks created in this algorithm are complete (in the sense of our simulator). The actual daily schedule *DS(ind,rd)* created for every simulated individual *ind* and for every day *rd* can be directly sent to the agents in the simulator. Every day of the simulation, the agents will receive their tasks, and they will decide how they are going to perform them.

3.7 Validation Methodology

This model has been implemented and is currently being tested with the data from the INSEE TUS. The next step is to validate the result of the produced simulation.

Several methods are possible. First, we would like to verify that the autonomy of the agents does not harm the macroscopic realism of the simulated behaviors. Indeed, as we generate non-scripted schedules, the agents have some degree of freedom to reorganize them. That can be checked by launching a large number of simulations and generate the TUS timetables associated with each day of simulation. Then we can compute the statistical results at a macroscopic level from these new timetables as if they were real ones, and finally compare them with the real ones. This method is easy to perform (it only relies on computation time), but like the validation of the statistical methods, only verifies the realism of the activities at a macroscopic scale.

A second verification is to compare real and simulated activities at a microscopic level. However, we cannot manually verify a large number of produced behaviors. Our proposed approach is to generate “new TUS timetables” as in the previous method and to perform a classification process with the real TUS timetables and the simulated ones. Based on previous work (Darty et al. 2014), we claim that if the obtained clusters are mixed (they contain both real timetables and simulated ones), it means that the simulated activities are indistinguishable from real ones, based on the considered variables. However, we still need to define the relevant classification variables. That will allow us to state that the individual simulated activities are “realistic”.

4 CONCLUSION AND PERSPECTIVES

We have presented a multi agent model using concepts coming from statistical methods of human activity generation. In particular, thanks to data collected in TUS, we are able to calibrate the simulated behaviors. This model has two major advantages. First, compared to traditional statistical methods, it allows the generation of more realistic individual behaviors, while keeping the same quality of realism at a macroscopic level. Second, compared to more traditional MABS, the use of TUS allows the objective measurement of the realism of the simulated activities. In addition, the international and generic nature of TUS makes them usable in various application domains.

The next step of our work is to implement this model on data collected within our project to study the realism of the behavior simulated.

This work leads to many perspectives. In the field of energy simulation, adding reactivity and autonomy to the simulated individuals allows the prediction of long-term consumption, and the ability to take into account the impact of new types of consumption (generalization of electric cars, self-production and self-consumption of electricity, etc.). One also becomes able to deal with major events (climatic, social, etc.). Another research track currently followed by our team is to study the impact of new electrical tariff on consumption. How do consumers react to a change in the price of electricity?

In the area of MABS, the widespread use of TUS could bring a better understanding of the relationship between the notions of realism and credibility (some of the actual behaviors observed in the TUS seem highly unlikely or even incomprehensible). Furthermore, the worldwide nature of TUS can also help modellers to introduce, in a consistent and measurable way, some lesser explored aspects of human activity simulation (such as the individual's culture or other local specificity).

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