Simulation of home daily activities for lifestyle monitoring systems development

Fabien Cardinaux, Simon Brownsell, David Bradley and Mark S. Hawley

***Abstract*— Lifestyle monitoring (LM) technology is part of a new generation of telecare which aims to observe the daily activities of older or vulnerable individuals and hence determine if an intervention may be beneficial. The development and validation of new LM systems should ideally involve extensive trials with users in real conditions. Unfortunately, effective user trials are very challenging, generally limited in scope and very costly. In this paper, a simulator is proposed that can serve to generate synthetic data of daily activity which could then be used as a tool for the validation and development of LM systems. The most challenging part of the simulator is to replicate people's behaviour. In the paper, a novel model of daily activity simulation is proposed. Such daily activities are dependent on a number of external factors that control the need or desire to perform the activity. The proposed simulator aims to reproduce behaviour such that the probability of performing an activity increases until the need is fulfilled. It is possible to parameterise the behavioural model according to a set of features representing a particular individual. Experimental verification that the desired features are reasonably reproduced by the simulator is provided.**

***Index Terms*— Simulation, Lifestyle Monitoring, Daily Activities, Telecare.**

I. Introduction

LIFESTYLE MONITORING is an approach that is increasingly being considered by health and care services to maintain older and vulnerable people in their home. As part of the newer generations of telecare, lifestyle monitoring (LM) aims to observe the activities of older or vulnerable individuals and if circumstances change determine if an intervention may be beneficial. Generally, LM uses a set of sensors fitted in the house and aims to detect those deviations from 'normal' behaviour that could be indicative of a change in care needs (e.g. Mobility problems, difficulty of toileting, etc.). The development and validation of such a system should ideally involve trials with users in real situations. Unfortunately, establishing an effective user trial is a very challenging operation that is often limited in scope: a literature review [4] shows that only 4 trials have been conducted with more than 20 persons. In this paper, a simulator is proposed that can serve to generate synthetic data of daily activity which could be used as a tool for the validation and development of LM systems.

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The aim is to develop a simulator that can generate a realistic sequence of daily activities, and then the subsequent response of a lifestyle monitoring system. The model must allow for changes to key parameters, so that it can simulate circumstances such as a reduction in mobility or illness that could lead to a change in care need. The simulation would then be used to generate the relevant data and hence to check if the LM system can accurately respond to the changes. The simulation could also serve other purposes, as for instance to evaluate the effect of a new type of sensor before physically integrating it and by consequence significantly reduce development costs.

While this paper provides an overview of a possible complete simulation system, it focuses in particular on the simulation of daily activities as this can be considered as the most challenging aspect. Indeed, the activities undertaken by an individual during a day are driven by a number of factors and unlike machines, human behaviour can be unpredictable. In terms of the simulation this unpredictability is reproduced through the use of stochastic models.

The motivations for and benefits of using a simulator and generated synthetic data for the development of LM systems are presented initially. The proposed hierarchical approach to simulate daily activities, actions and sensor events is then presented.

II. Background and Motivation

In England, over the next fifty years, the number of people over 65 is expected to rise by 56% and a similar trend is observed in most other western countries. As a consequence, numbers of researchers and governments are looking at novel solutions to support people in their own home by monitoring their daily activities [1,2,5,7,10,12]. How ever, most of the research publications in this domain present results based on only a small number of users. Indeed, a review of the literature suggests that to the end of 2009 only 4 trials have been conducted with more than 20 participants [4]. The limited scale and scope of trials can largely be attributed to the difficulty of performing such experiments. Indeed, while it is desirable to evaluate a lifestyle monitoring system under real conditions, several issues generally arise which act to limit the scope of the trials. These include:

a. Difficulty in recruiting participants who will accept a relatively intrusive system installation in their home without direct immediate return.
b. The system should be installed and data observed over a long period of time.
c. Difficulties in collecting ground-truth information. Indeed, to validate and develop a system that is supposed

to observe individual activity, it is essential to know which activity that individual is actually involved in at any time. This information could be collected by means of diaries, but these are not always accurate and can be very demanding for the participants if they need to be maintained over a long period of time. Another approach could be to visually monitor and manually annotate individual activity using video cameras on site, but this can be considered to be too intrusive and would require a laborious video transcription and annotation phase.

d. In order to validate a system that aims to detect abnormality, a significant number of abnormal events must be observed. By definition, such abnormal events are rare and when a trial is conducted, it is therefore unlikely that these abnormal events occur frequently.

Given these constrains, it becomes clear that trials with users, while ultimately essential, will generally be limited in scope. As a consequence, thorough and large scale testing on synthetic data can be of great benefit to the development of novel LM systems.

By using a simulation tool, it becomes possible to simulate virtually any condition, and it becomes possible to test the effect of any change on the system or on subject behaviour. With a simulator it is possible to create a change in behaviour on demand, rather than running a real system while hoping to encounter specific types of change. Likewise, a simulator could provide information on the effect of including a new sensor (with known specifications) in the system before having to encounter the costs in both time and money of real world experiments.

Verone et al [11] attempted to simulate behavioural data from a patient living in an intelligent home[1]. Their paper presents some interesting ideas and appears to provide a useful background in developing the simulator being proposed here. However, Verone et al only simulate room transitions based on daily behaviour profiles. More importantly, they do not propose any mechanism to modify behaviour according to specific changes in the subject's condition or care need.

III. Simulation approach

The primary objective of the simulator is to generate data that can be used for evaluating the performance of a LM system and should be able to reproduce sensor activations that correspond to specific user behaviours. Note that there is a differentiation between those key features which are characteristic of behaviour or the system and those key parameters that translate these features into the values used for the simulation. Key features could for example be the number of times the subject has a drink in a day, the average time the individual takes for lunch or the expected error rate of a sensor. Key parameters are model parameters that reproduce these features. Some of these features can change with time, in particular when circumstances that result in a change in care needs is simulated.

[1]Habitats Intelligents pour la Santé

It can be assumed that individual behaviour is independent of the LM system, and therefore can be generated independently. The simulator can therefore be decomposed in two parts. The first part simulating individual behaviour and the second simulating the response of the LM system to these behaviours. Moreover, the simulation will be based on configurable parameters based on the key features that it is desired to simulate. Fig. 1 thus represents the structure of the simulation system.

A. *Simulation of behaviour*

Individual behaviour can be decomposed into two hierarchical levels. The first of these levels is the activity sequence, defining **WHAT** they are doing. The second level is then a sequence of actions, defining **HOW** they are doing it. For example, having dinner is an activity and turning the kettle on, opening the fridge, sitting on a chair and so on could be the associated actions. While activities are enduring events, actions are considered as instantaneous and are not associated with any duration.

This hierarchical structure was chosen for the simulator in order to imitate human behaviour in that individuals tend to decide what they want to do (activities) according to a number of motivating factors and then to do it in a defined way (actions).

Simulating realistic daily activities is a challenging task since activities performed are usually driven by a large set of factors. These include; basic needs, lifestyle, weather, TV programming, family visits among many others. The proposed approach to generating the sequence of daily activities is described in detail in section IV.

Knowing that the subject is involved in a particular activity, it is possible to generate the corresponding set of actions. In practice, it is assumed that an activity follows a specific set of actions separated by a time interval. While the set of actions is fixed, the time interval between actions is randomly sampled from a probability density function (PDF). The parameters of the PDF are set for each interval between actions according to the expected time intervals and their variances. Note that it can be envisaged that in future versions of the simulator that several ways of performing a specific activity would be incorporated, for instance through the incorporation of a randomisation of a sequence of actions.

Room Transitions

Transitions between rooms requires special consideration. As an example, if an activity requires the subject to go to the kitchen, the exact room transitions to execute the "*go to kitchen*" action will be defined with respect to the subject's initial location. The initial location can only be known at run time since it depends on the location of the previous activity. To determine the sequence of room transitions at run time, graph theory is used. The house layout is coded as an undirected graph where edges are the locations and vertices are the possible transitions between locations. In order to travel from one location to another, the subject is assumed to use the shortest route, in terms of numbers of locations visited. Optimised search for the shortest path is a well known problem in graph theory and standard algorithms such as

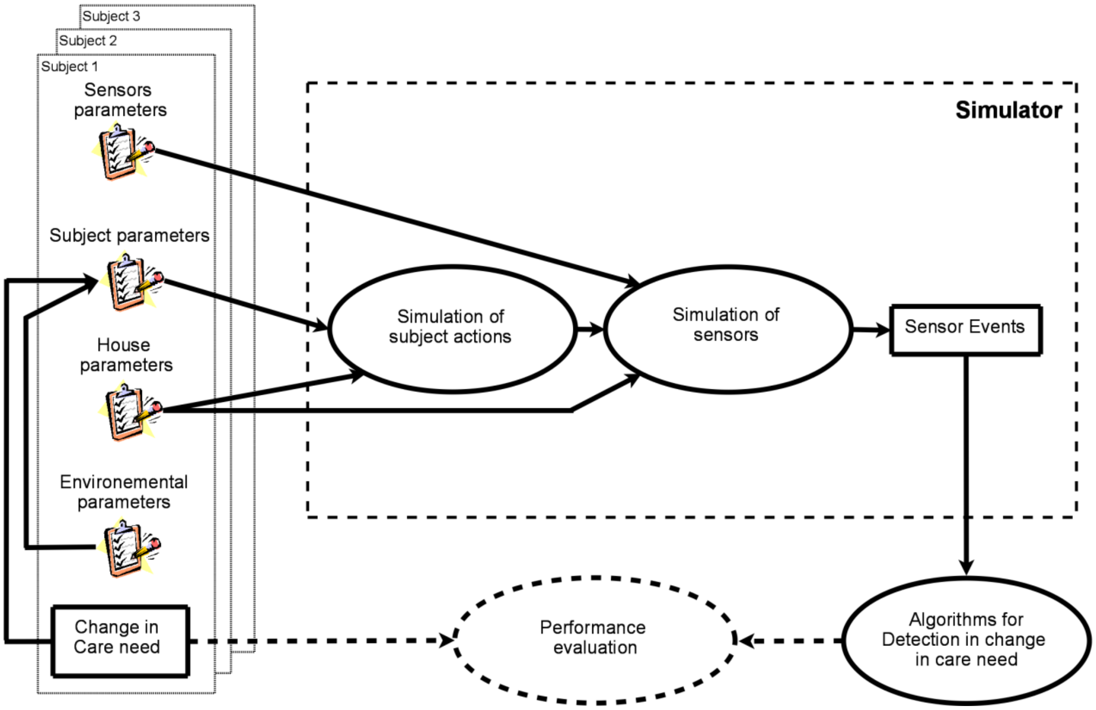

Figure 1- *Simulation scheme: Change in care needs can represent a change in person health or physical condition and is going to affect the subject's parameters. The change in subject's parameters is going to affect the output of the simulator (sensor events) and the algorithms can be validated by matching the simulated changes and the detection of these changes by the algorithms.*

Dijkastra's algorithm [6] are used for this task. When the sequence of locations visited is found, the transitions are timed proportionally to the walking speed of the subject. This latter is a subject parameter that can be changed to emulate behavioural changes.

Run time parameter adaptation

Note that transition rates and times are initially set to a standard value, but this value can then be modified at run time according to factors such as a change in the subject's health status or an environmental change (see Section III.C). Parameters can also be affected by events that have occurred in previous days. For example, a rule could be set to reduce the probability of going out shopping if the "*going out shopping*" action has been activated within the last three days. By doing so, it is possible to generate levels of dependency between actions performed in a day and actions performed in previous days, enabling simple weekly routines to be generated.

B. System simulation

Lifestyle monitoring systems include both hardware and software elements. The hardware element is the set of sensors deployed along with the communication platform while the software element is the algorithms that interpret the sensor data to generate a response. This software element does not require any simulation as the actual algorithms can be executed. Both the sensors and communication platform can be simulated using the generated set of actions and a set of rules that defines the sensors responses to specific actions.

According to the functionality and characteristics of the simulated sensors, the ideal response to an action is defined as well as possible sensor errors. Generally, a sensor will respond to a specific action: for example, a door sensor will generate an "open" event when the door is opened and a "close" event when the door is closed. Then according to the specification of the sensor or test performed on this sensor, it is possible to estimate the probability of missing the event, the probability of generating events when nothing actually happens or to introduce a delay between the action and the sensor detecting it. These characteristics can be included in the simulator.

C. Features and parameters

The simulator must be able to simulate both individual and system behaviour according to a number of features. For example, a feature associated with the "having dinner" activity could be the average time of day the subject has dinner. These features must then be transposed to model parameters, so that the data generated by the simulator reproduces the same features.

These features are not necessarily constant and can be set to change while the simulation is running. In particular, it is desired to be able to simulate changes that can be associated with a change in care need (e.g. deterioration of mobility or illness). Features, and consequently parameters, will be altered by this change in a predefined way. As a result, the data generated by the simulator will be affected and it is possible to analyse the response of the LM algorithms to these changes.

As an example, it might be expected that a relatively benign illness such as a cold would increase the time spent in bed, reduce the probability of going out and so forth. Such an illness may also have differing degrees of severity that can change from day to day.

In order to be able to simulate this condition, the way a change affects a feature is weighted by a *severity* variable $S_{cold} \in [0,1]$. Thus, $S_{cold} = 0$ means the absnce of a cold and $S_{cold} = 1$ means that the severity is a maximum.

In the previous example, the average time spent in bed could be affected by the cold in the following way:

$$T_{bed} = T_{bed}^{std} + S_{cold} * \eta \quad (1)$$

Where T_{bed}^{std} is the expected time spent in bed in a standard situation, T_{bed} is the actual expected time spent in bed and η is constant that regulates the effect of a cold on the time spent in bed. η can be seen as the additional time spent in bed with a cold of severity maximum.

The way such a variable changes can be by following a specific functions. Some examples of the *severity function* associated with particular conditions could be:

- Affine function to simulate a regular trend of degradation or improvement.
- Sinusoid function to simulate a cyclic condition with periodical behaviour.
- Exponential function to simulate an exponential degradation or improvement.
- Combination of sinusoid and affine function to simulate a general trend of improvement or degradation with periodic local variation.
- Affine function and white noise to simulate a general trend of improvement or degradation with some random local variations.
- A parabolic function to simulate a temporary condition (e.g. cold or a flue).

In order to make the simulation more realistic, it is possible to simulate other types of change related to external factors such as the weather, the TV programme schedule or day of the week. These can affect the subject parameters using the same mechanism as previously defined. However, while they do not represent any change in care need they do represent realistic changes in profile that LM algorithms should be able to handle appropriately.

IV. Simulation of Daily Activity

The simulation of daily activity consists of the generation of the sequence of activities performed by an individual. Because of the dynamic nature of the daily activity simulation, it is necessary to keep track of the current value of the simulated time as the simulation proceeds. The simulation clock is a variable that gives the current value of time which is then incremented by a fixed value. The unit of the increment can be chosen according to the level of precision needed.

As previously stated, daily activities are dependant on a number of external factors that control the need or desire to perform them. Arguably, a desire can be the consequence of a need, generalised here by using the word *need* even though in some cases *desire* could be considered more appropriate.

The aim is to build a simple model of the need to perform a specific activity. It provides at each time the probability of acting on a need. The main assumption of the proposed model is that the need to perform a specific activity will increase with time until the need is fulfilled and the activity is performed. Figure 2 presents the simplest form of the need model where the probability of performing an activity increases linearly with time. This model can be defined such that:

$$p_t = \lambda . t \text{ when } 0 < t < \frac{1}{\lambda}$$

And $$p_t = 1 \text{ when } t \geq \frac{1}{\lambda} \quad (2)$$

where p_t is the probability of performing an activity at time t and λ is the single parameter regulating the model.

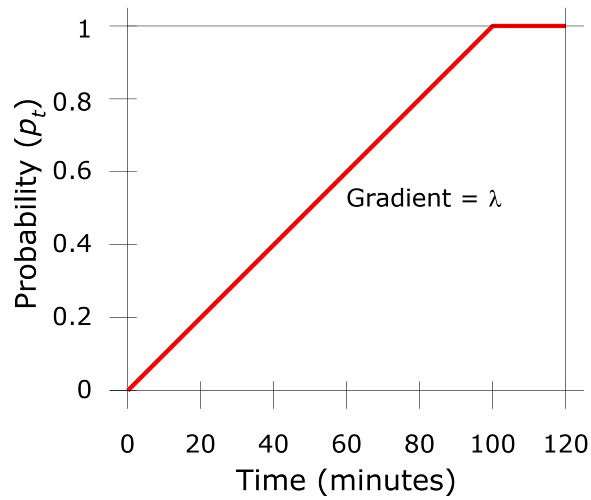

Figure 2 - *Representation of a linear need model where the probability p of performing an activity increases linearly with time*

At each time interval it is randomly decided if an activity with the probability p_t is to be performed or not. From a probabilistic point of view, a Bernoulli Trial is performed with a probability of "success" of p_t where "success" means that the activity is performed.

When an activity is performed at time T, it is assumed that the need is fulfilled and the probability of performing the activity at time T+1 is returned to zero and starts again to increase with gradient λ from this point. Fig. 3 then represents the evolution of p_τ for an activity that is repeated throughout the day.

The *need* model can be used in different ways to simulate different activities. For example, for an activity that is repeated at regular intervals throughout the day, the behaviour represented by Fig. 3 can be produced: when the activity is performed the value of p returns to zero and starts again to increase linearly until the activity is performed again. Other types of activity include those that are normally associated with a specific time of day, as for instance having dinner. In this case, *p* remains to zero until a defined time of day when it starts to increase until the activity is performed. Note that, in this case, the time when the activity starts to increase can be considered as a second parameter (the first parameter being the gradient λ).

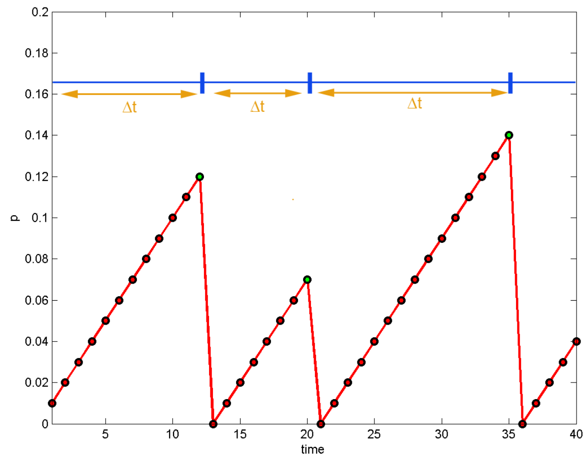

Figure 3 - *Evolution of the probability of performing an activity with regard to the time of day. At each time interval it is randomly tested as to whether the activity is performed using the probability of occurrence p. Δt corresponds to the time interval between two occurrences of the activity.*

In the former case, the feature that serves to define the parameter λ could be the average frequency of the activity and in the second case it may be the average and variance of the time of day the activity starts.

Note that when λ is large, the probability, p_t, of the activity to occur increases more rapidly and as a consequence, the expected time Δ*t* before the action is performed is reduced. In order to set up the simulator, it is useful to formally establish the link between λ and Δt. Indeed, it may be desired to set the system such that an activity occurs at a specific frequency on average. A mathematical description of the model is thus necessary to define the relationship between λ and the probability distribution of Δ*t*.

At each time interval a Bernoulli Trial probability of success p_t is calculated using equation 2. It is decided if the activity is performed or not according to probability p_t when Δ*t* is the time lapse (number of time units) before the activity is performed. Thus Δ*t* has values in the range {1, 2…., 1/λ} since $p_t = 1$ when $t = 1/\lambda$. The probability distribution of Δ*t* is defined as:

$$p\{\Delta t = k\} = p_k \prod_{t=1}^{k-1} (1 - p_t) \quad (3)$$

$$= \lambda.k \prod_{t=1}^{k-1} (1 - \lambda.t) \quad (4)$$

$$= p_k \prod_{t=1}^{k-1} (1 - p_t) \quad (5)$$

$$= \lambda.k\lambda^{k-1} \prod_{t=1}^{k-1} \left(\frac{1}{\lambda} - t\right) \quad (6)$$

If λ ∈ *N* then,

$$p\{\Delta t = k\} = \lambda^{k+1}.k.k!\binom{1/\lambda}{k} \; \forall\, 0 < k < 1/\lambda \quad (7)$$

where $\binom{1/\lambda}{k}$ denotes the binomial coefficient.

By definition the expected value of Δ*t* is:

$$E[\Delta t] = \sum_{k=1}^{k<1/\lambda} k.p(\Delta t = k) \quad (8)$$

and its variance is:

$$Var(\Delta t) = \sum_{k=1}^{k<1/\lambda} k^2.p(\Delta t = k) - E[\Delta t]^2 \quad (9)$$

Equations 8 and 9 can then be used to calculate the expectation and the variance of Δ*t*. A lookup table is built with reasonable values of λ associated with the corresponding expectation and variance. Then, when the simulator is to be set for a specific value of expectation or variance, it is possible to refer to the closest value in the lookup table to estimate a suitable parameter value for λ.

V. SIMULATOR SETUP

The proposed simulator includes a large number of parameters and the development of the simulation must comprise a parameterisation step. As shown in Fig.1 the parameters are clustered in four categories:

- Subject parameters - Parameters related to the subject's behaviour. These include:
  - ⇒ List of activities.
  - ⇒ Activities parameters: average frequency of occurrence if they are repeated activities or the mean and variance of the time they occur if they normally happen around a particular time of day.
  - ⇒ The sequence of actions which are associated with each activity as well as the average time lapse between actions.
- Sensor parameters - Sensors rules that are used to infer sensor event from a subject's actions. These include:
  - ⇒ List of sensors
  - ⇒ Rules of activation
  - ⇒ Mis-detection rates
  - ⇒ Frequency of spurious events and probability of occurrence, mean and standard deviation of delay.
- Change parameters – Including:
  - ⇒ List of factors that imply a change in care need.
  - ⇒ Definition of functions that define how the model is affected by factors that imply a change in care need.

- Environmental parameters - External parameters that can affect a subject's behaviour but are not directly related to the subject: Including:
  - ⇒ Weather
  - ⇒ Day of the week
  - ⇒ Television programme schedules
  - ⇒ Definition of functions that define how the model is affected by environmental factors.

The above parameters represent our simulator, other aspects should be defined according to specific needs of the simulator usage. The simulation parameters must reflect characteristics of the real world and ideally should be inferred from experiments. Two experiments were set-up to gather information and set simulator parameters:

- Experiments conducted in a simulated dwelling where subjects were asked to perform specific activity or actions. These experiments allowed us to estimate the expected error rates of the sensors as well as estimating the expected time lapse between actions within a particular activity.
- Experiments conducted with four older people for at least 18 weeks where diaries and questionnaires were used to record activities and events. These experiments were used to setup the activities parameters of the simulator.

However, for practical reasons, it cannot be expected that all parameters can be inferred from these experiments. The other parameters can be evaluated by expert knowledge.

VI. Model Verification

Simulation model verification is often defined by reference to Sargent [8] as "*ensuring that the computer program of the computerised model and its implementation are correct*". A formal definition of model validation is given by Schlesinger et al [9]: "*substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model*".

For the daily activity simulator, there is no set of specific tests that can be applied to determine the absolute "correctness" of the model. It is, however, possible to check if the simulator model meets specifications and that it fulfils its intended purpose. In particular, it is possible to verify that a user set of parameters are reflected in the simulated data. Indeed, because of the approximation made to find λ for specified simulation parameters and the assumption that activities are independent some difference between specified and observed parameters are expected to be observed.

Independent activity testing – Here activities are generated independently with only one type of activity being generated at a time, and hence not dependent on any other activity. The validity of the simulation of activities that are repeated throughout the day was checked using the "drinking" activity. The main feature of this activity is its frequency, the average number of time it occurs per day (*n_day*). Table 1 reports on the expected and corresponding observed behaviour when 1,000 days have been simulated.

Table 1 *Expected and observed averages of the number of times the activity is repeated during the day when simulated over 1000 days*

Expected	**Observed**
n_day	**Average(n_day)**
1	1.015
2	2.000
4	4.026
8	8.001
16	15.900
32	31.692

Then, an example of activity that usually happens around a specific time of day was considered, in this case the "lunch" activity is simulated. The main features associated with this activity are the average and the standard deviation (std) of the time of day the activity occurs (time) and the probability of activity occurrence (*p*). Table 2 shows the expected and corresponding observed behaviours when 1,000 days have been simulated.

Table 2: *Expected and observed features of an activity occurring around a specific time of day when simulated over 1000 days*

Expected			**Observed**		
time	**std (time)**	**p**	**Average (time)**	**std (time)**	**p**
12:00:00	0min	1	12:00:00	0.0min	1.000
12:00:00	10min	1	11:59:53	9.8min	1.000
12:00:00	20min	1	12:00:46	20.0min	1.000
12:00:00	40min	1	12:01:49	41.3min	1.000
12:30:00	20min	1	12:31:20	20.9min	1.000
12:00:00	20min	0.9	12:00:45	20.2min	0.899
12:00:00	20min	0.5	12:00:32	20.7min	0.493
12:00:00	20min	0.1	12:03:55	21.3min	0.099

Integration testing - Previous testing checked that it is possible to observe expected results when activities are generated independently. A similar test was then performed when all activities were generated together and including dependency between activities.

If an activity is to be started while another activity is being performed, the new activity enters a First In First Out (FIFO) "*waiting list*" and will actually start when current activity and other activities in the waiting list are finished. Consequently, the new activity will not start at the time selected by the need model and it can generate differences between expected and observed features.

We define the "time active" as the total time spent in any activity. It is anticipated that the longer the time active, the more the observed activity occurrences are expected to coincide with other activities. The time active can be seen as how busy the user is. As in the previous experiment, expected outcomes were compared with the observed features. This time we want to observe the effect of the other activities, therefore the amount of other activity generated is measured as the total expected time spent performing any activities during the day (time active). Table 3 reports on the expected and observed number of times the drinking activity is performed during a day along with the time active. The other activities parameters are changed in order to vary the total amount of time the subject is active during a day. Table 4 then shows the outcomes of the tests for the lunch activity where the expected time of day (time) is shown together with the associated standard deviation and the daily probability of the activity are again compared with observed values.

Table 3 *Expected and observed average number of times the activity is repeated along the day. Time active is the total expected time spent in any activity during a day when simulated over 1000 days*

Expected		Observed
n_day	**Time active (min)**	**n_day**
1	685	1.366
8	744	8.242
32	946	28.081
8	596	8.284
8	872	8.163
8	1035	8.063

Table 4 *Expected and observed features of an activity that occurs around a specific time of day. Time active is the total expected time spent in any activity during a day when simulated over 1000 days*

Expected			Observed	
time	**Std (time)**	**Time active (min)**	**Average (time)**	**Std (time)**
12:00:00	0min	761	12:01:34	8.52min
12:00:00	20min	761	12:01:30	22.54min
12:00:00	40min	761	11:58:33	39.65min
12:00:00	20min	562	12:00:25	21.18min
12:00:00	20min	1273	12:07:26	25.21min

Generally, the observed values are reasonably close to the expected values. This is particularly true when the activities are generated independently, which suggest that the model have been correctly implemented. As expected, when all activities are generated at the same time and under particular extreme conditions, there is a larger discrepancy between observed and expected value. This is the case when:

- an activity is expected to be repeated a many times throughout the day.
- the variability of an activity is set to be 0. While it is expected that the activity arises always at the same time of day, in practice, variability arises when some other activities are performed at the time when the activity is supposed to occur.
- when the generated activities are almost filling the 24 hours of the day. In this case, since it is assumed that only one activity can be performed at a time, the activity will happen when there is "free time" and by consequence will not necessarily exactly respect the expected time of occurrence.

As a consequence, if the application of the simulator requires the production of precise features such as the average time of day the activity occurs, it is recommended to set the parameters to stay outside these conditions. However, for the purpose intended by this simulator, the validation experiments suggest that the observed results are reasonable and can be used as such.

These experiments suggest that the computer programming and implementation of the conceptual model is correct and shows the limitation of the model in some particular and known conditions.

In additions to the controlled model verification presented in this section, a lifestyle monitoring system[2] has been installed with four older people. They have recorded thier activities in a diary for at least 6 weeks. We used the collected diaries and the lifestyle monitoring system specification to setup the simulator and thus generate a large amount of synthetic data.

VII. LIMITATIONS

It is believed that the proposed model is satisfactory for the intended application however it can be considered to suffer from number of limitations for a more realistic simulation of daily activities that could be required in other applications.

The model is built to reproduce realistic statistical features, however it does not integrate firm limitations encountered in real life. For example, it might be impossible to go shopping after 8pm because the shop is closed. To cope with this problem the model must allow the possibility to integrate some 'hard rules' into the model.

Furthermore, if the simulator needs to be highly realistic, the degree to which the synthetic daily activities resemble real life activities should be evaluated. A face validity test [8] could be performed where knowledgeable persons assess whether the model's behaviour is reasonable.

VIII. CONCLUSION

An important barrier for the development of the next generation of intelligent telecare systems [3, 13] is the difficulty of performing effective field evaluations. Consequently, the pre-evaluation of such systems using synthetic data would be beneficial. In this context a functional simulator of a lifestyle monitoring system is proposed with a particular emphasis on the development of a new simulation model of daily activity. The proposed simulator can be parameterised to simulate specific individuals or sets of sensors. The performed experiments show that the simulator is able to reproduce data containing the desired features and is thus now being used in the development of LM algortithms.

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[2] Tunstall Lifeline Connect+ : http://www.tunstall.co.uk

author(s) and not necessarily those of the NHS, the National Health for Health Research, or the Department of Health.

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