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Methods for the prediction of intermediate activities by office occupants

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ABSTRACT

Computer models for building usage simulation are needed that produce detailed data about activities of members of an organization for accurate building evaluation. Intermediate activities that interrupt the planned activities play an important role but are often ignored in existing simulations. A model is proposed to predict the occurrence and the frequency of intermediate activities during an office working day. Two prediction methods are presented, namely probabilistic and S-curve. The applicability of each method depends on the characteristics of the intermediate activity. Through an experiment data were collected about intermediate activity behavior in an office. From these data conclusions are drawn on the validity of the prediction methods. Finally for each intermediate activity the formulas are presented including the parameter values that are analyzed from the experiment. The formula can be used in office evaluations that require detailed input data on occupant activities.

1. Human behavior modeling in office buildings

Human behavior modeling has its roots in the social sciences. The emergence of environmental psychology in the 1960s manifested this research domain. At that time environmental psychologists assumed a straightforward relationship between the physical setting and human behavior. Human behavior in these early studies was often narrowed down to job satisfaction. However, the influence of the physical environment on job satisfaction showed very diverse results [1–5] indicating a limited validity. More recently human behavior is researched in a broader perspective not only by social scientists but also by engineers. Human behavior in this research is explained from two basic needs, namely physical needs and psychological needs. Physical needs can be differentiated into: space, light, climate conditions and sound. Research has shown that physical needs are highly individual [6]. Psychological needs are divided into: interaction, privacy and personalization. Obviously these needs are highly individual too. Nevertheless environmental conditions are usually fixed (floor layout) or marginally adjustable (climate system) which causes a lot of discomfort and stress in buildings like offices. Not surprisingly engineers now also research human behavior in the built environment because they need models for implementation in control systems. These systems respond to human behavior and/or anticipate human behavior (e.g. temperature, motion detection). Architectural research does not focus on behavior modeling but on the perception of space. A well know method from this field is Space Syntax originally developed by [7]. By analyzing the floor plan layout a metrics is deduced that is used to predict how people will move through space. Business management has added another dimension to human behavior, namely the organizational point of view. In business process modeling, work processes are designed for optimal performance of the organization, thereby affecting the employee's behavior in space.

Building performance simulation models usually focus on the calculation of physical conditions (temperature, humidity) dependent on the spatial dimensions, material use and installed installation systems. Human behavior is described in terms of activities and sometimes in terms of user control of the installation systems. Recently models have been developed by Rijal et al. [8], Mahdavi et al. [9], Nicol [10], Reinhart [11], Bourgeois [12] and others to include human behavior in building performance analyses. The human behavior part of these models is usually based on empirical data. These data are used in algorithms to define the activity type (office work, etc.), number of occupants/M2, occupant mobility/hour, and windows and lighting control type (manual or automated).

For a simple office room Hoes et al. [13] investigated what the effect of a more accurate user behavior model on the outcome of a buildings performance analysis. Therefore they compared the results of ESP-r used stand alone with ESP-r used in combination with the Sub-Hourly Occupancy Control (SHOCC) model developed by Bourgeois. The results from this research show that some of the investigated performance indicators are sensitive to the accuracy level of human behavior modeling. They found that especially heating demand (9%) and cooling demand (24%) deviate significantly between these two analyses. This outcome is in line with the

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Table 1
Types of intermediate activities.

Type	Occurrence depends on
Receive unexpected visitor	Role
Walk to printer	Role
Walk to mailbox	Role
Have lunch	Time, Activity type, Type-of-day
Sport (during workday)	Time, Activity type, Type-of-day
Get a drink	Time, Activity type, Type-of-day
Smoke (not at workplace)	Time, Activity type, Type-of-day
Have a break	Time, Activity type, Type-of-day
Go to toilet	Gender and age

Table 2
Prediction method.

Type	Prediction method
Have lunch	S-curve
Sport (during workday)	S-curve
Get a drink	S-curve
Smoke (not at workplace)	S-curve
Have a break	S-curve
Go to toilet	Probabilistic
Receive unexpected visitor	Probabilistic
Walk to printer	Probabilistic
Walk to mailbox	Probabilistic

findings of Degelman [14] who states that building simulation is only capable of accurate predictions if building use is predictable.

Recently in human behavior simulation research there is a trend towards activity based modeling. The premise in this research is not to simplify real behavior to overcome computer programming or capacity problems, but to model real life behavior in all its complexity as closely as possible. The research presented in this paper fits in this trend. The research domain is office buildings because data are relatively easily accessible for these buildings and their occupants. The purpose of the model is to predict human activities including movement in office space, based on organizational data and a 3D office floor layout. Accurate simulation of human behavior can improve and/or extend existing simulation models by providing more detailed and validated data. In the proposed model for human behavior simulation a distinction is made between skeleton activities and intermediate activities [15]. Skeleton activities depend on the role of a person in the organization and are usually defined in his/her functional description (e.g. chair meeting, give lesson, etc.). Intermediate activities depend on a person's role to a lesser degree but have a strong relationship with the psychological and physical needs (e.g. get a drink). Intermediate activities interrupt skeleton activities but are deemed important for the well-being of the office employee.

In this paper we focus on intermediate activities because to a large extend they are independent from a specific office organization and thus the developed prediction methods are very generic. The prediction methods can easily be integrated with any model that requires appropriate data on intermediate activities, such as building performance models, facility management models, workplace assessment models, etc. The outline of the article is as follows. First we define the types of intermediate activities in an office organization, we present our methodology for the prediction of the occurrence of these types of activities in time and we explain our research method. In the next section the frequencies and durations of the intermediate activities are presented. Following, the so-called S-curves are estimated for prediction of the intermediate activity occurrence in time. In the results section the prediction formulas and their estimated parameters are presented. Finally conclusions are drawn on the applied methodology and the effect of the intermediate activity estimates in building evaluation models.

2. Intermediate activities

Intermediate activities were analyzed as follows. Members of the research group (8 persons) were asked to write down all triggers that made them move trough space excluding those that originated from work tasks. From this small survey 9 intermediate activities were retrieved. From the list and the number of occurrences for each person we analyzed that two main categories can be discriminated, namely intermediate activities that have a strong correlation with the role of a person and intermediate activities that have a weak correlation with a person's role (Table 1). Moreover for the last category we anticipated that occurrence depends on the following parameters: (1) time elapsed since start or last occurrence, (2) the activity type of the skeleton activity that would be interrupted and (3) if it was a day mainly consisting of concentrated work or attending meetings. An exception is the activity 'go to toilet'. In an experiment these parameters, amongst others needed to be asked from the subjects. Although the activity 'go to toilet' also fell in the last category, it was felt indecent to ask how many times a subject uses the toilet. Therefore the dependency parameters for this activity were set to gender and age.

3. Prediction of activity occurrences

Scheduling the intermediate activities is done using two different methods, namely the S-curve method and the probabilistic method. For each activity we have made an assumption on the most appropriate occurrence prediction method based on their characteristics. The S-curve method is appropriate for those activities that strongly depend on the time elapsed since the previous occurrence.

Example. The longer ago an employee performed the activity get a drink or smoke, the more urgent this activity becomes due to physiological reasons.

Other activities occur more or less randomly during a workday, like receive an unexpected guest (see Table 1). So, instead of using an S-curve function, a random function is used to determine the start time of this type of activities. With this function the start time of these intermediate activities are randomly spread over the duration of the workday. The number of occurrences of each intermediate activity during a workday (the desired frequency) depends on an average frequency and a certain extent of variance (Table 2).

3.1. S-curve

For this type of activities it is assumed that satisfying the need of an activity yields a utility. In other words: an employee derives some utility from performing an activity. The utility of an activity increases with the progress of time since the previous occurrence of that activity; it becomes more urgent to perform this activity. An S-shape curve is assumed for the utility as function of time, suggested by [16]. The overall form of the S-shape is as follows: the rate of increase of the utility for each time step (marginal utility) is initially small and increases till its maximum value (inflection point), after which the marginal utility diminishes with time. The top asymptote (maximum utility of the activity) represents the utility derived from the activity if time increases indefinitely. The bottom asymptote (minimum value) represents the utility of an activity in its initial situation; this relates to the start of the working day or to the situation directly after performing the activity. The actual form

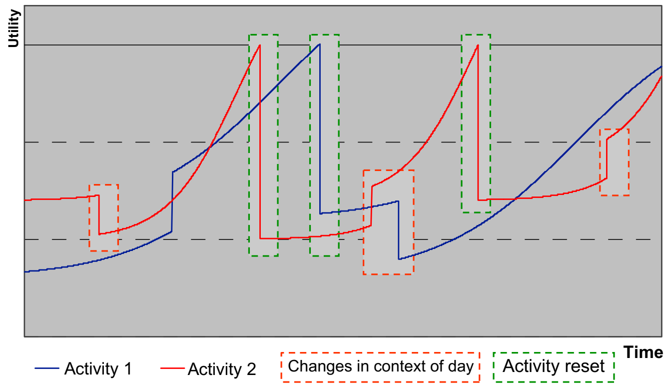

Fig. 1. The complex erratic shape of two S-curves taking into account changes in the context of the day and the performance of intermediate activities (activity reset).

of an S-shape is not the same for each activity; the form depends on the characteristics of the activity.

For determining the utility of activity a the following function is assumed:

$$U_a = V_a + C_a + \varepsilon_a \tag{1}$$

where: V_a is structural (or systematic) utility of activity a, ε_a is random utility (or error term), C_a is constant utility

The constant utility is the utility compared to the situation where the activity is not performed by an individual; the utility for not performing an activity is assumed to be zero.

For V_a the following S-curve function is assumed:

$$V_a = \left(V_{\min} + \frac{V_{\max}}{1 + \exp(\beta(\alpha - t))}\right) - V_{\text{context}} \tag{2}$$

where: V_a is structural utility of activity a as function of time t, $V_{\max}$ is maximum utility of activity a, β is slope of the S-curve, α is horizontal displacement of the S-curve, $V_{\min}$ is minimum utility of activity a, $V_{\text{context}} = \text{f(type-of-day, type-of-activity effect)}$.

Equation (2) determines the structural utility of an activity as a function time taking into account the context of the day. Time (t) represents the time elapsed since the previous occurrence of the activity a, or it represents the time elapsed since the start of the working day if the activity has yet to occur. The characteristics of the day, like previous performed activities, experienced pressure of time and the type-of-activity an employee is currently performing, influences the likelihood that an employee engages in an intermediate activity. The context is modeled using two effects, namely the type-of-day and type-of-activity effect (see Section 4). The two effects combined describe the context of the day for the occurrence of intermediate activities. The context of the day influences the structural utility level of an intermediate activity. It is represented by the V_{context} variable in equation (2).

An intermediate activity is executed by an employee at the exact moment in time when the total utility (i.e. the structural utility combined with the random utility and the constant utility) of this activity is zero. In other words, an employee performs intermediate activity a, when the following criterion is met:

$$U_a = V_a + C_a + \varepsilon_a = 0 \tag{3}$$

The shape of the curve of an intermediate activity type, i.e. the horizontal displacement (α) and the slope (β), and the context of the day (V_{context}) has an influence on the occurrence of this activity. Fig. 1 shows two S-curves belonging to two activities; the utility of activity 2 increases faster than activity 1, resulting in activity 2 being more often executed than activity 1. Due to the fact that the context of the day (V_{context}) varies during the day and due to the performance of intermediate activities (activity reset), the actual shapes of the S-curve belonging to these activities have an erratic shape.

4. Experiment

The data used to estimate the parameters of the S-curve and the probabilistic intermediate activities were collected using a web-based survey, mainly consisting of a stated choice experiment. The survey consisted of three parts. First, each respondent was presented a set of questions to gather information about his or her characteristics (e.g. year of birth, role within organization for which he is working and if he smokes and/or sports). The second part of the survey dealt with questions related to the frequency and the average duration of both S-curve and probabilistic intermediate activities. In the last and main part of the survey the choice scenarios related to one chosen S-curve intermediate activity were presented to the respondent. One of the S-curve intermediate activities comprising the survey was chosen at random while taking into account if the respondent smokes and/or sports. Then, based on the average frequency entered by the respondents for this activity they were assigned to one of the available sets of choice scenarios.

Each respondent was asked to enter the number of times he or she performed the S-curve and probabilistic intermediate activities during a working day. For the S-curve activities the respondent was also asked to enter the average duration of these activities; it was assumed that the average duration of these activities strongly vary per respondent. The duration of the probabilistic activities is assumed to vary less.

In a stated choice experiment each respondent was presented with a series of hypothetical choice scenarios. In each choice scenario comprising the stated choice experiment the respondent was asked to indicate the probability that he or she will perform the intermediate activity in a particular setting of a typical working day. In each choice scenario the setting of the working day was varied; in other words, each choice scenario described a different setting of a working day. However, each scenario followed the same outline, namely:

> The previous time you performed the activity [activity] is [time] ago.
> Your working day consists of mainly [type-of-day].
> You are currently busy with [type-of-activity].
> No other intermediate activity is urgent.
> Please, indicate the probability that you will perform this activity right now (0 = certainly not, 100 = certainly yes).

Each choice scenario was described using a combination of levels of the following three attributes:

x_i Type-of-day effect (2 levels)
- Working day mainly consisting of work related activities (corresponds to null situation) [x_0].
- Working day mainly consisting of activities of the activity-type *meeting* [x_1].

y_j Type-of-activity effect (4 levels)
- Activity-type is *work* (corresponds to null situation) [y_0].
- Activity-type is *concentrated work* [y_1].
- Activity-type is *meeting* and the respondent is not the initiator of this activity [y_2].
- Activity-type is *meeting* and the respondent is the initiator of this activity [y_3]

z_k Time effect (4 levels)
- Longest elapsed time (corresponds to null situation) [z_0].
- Second longest elapsed time [z_1].
- Third longest elapsed time [z_2].
- Shortest elapsed time [z_3].

Table 3
Frequency of probabilistic intermediate activities.

Probabilistic intermediate activity	Frequency	
	Mean	Standard deviation
Go to toilet	2.78	1.14
Receive unexpected visitor	2.20	2.00
Walk to mailbox	1.28	1.06
Walk to printer	3.96	1.76

Table 4
Duration and frequency of S-curve intermediate activities.

S-curve intermediate activity	Duration		Frequency	
	Mean (mm:ss)	Standard deviation	Mean	Standard deviation
Have lunch	27:42	10:04	0.91	0.29
Sport	42:49	10:29	0.82	0.39
Get a drink	02:46	02:24	3.80	1.37
Smoke	06:00	02:36	2.22	1.64
Have a break	08:06	06:39	2.51	1.47

A full fractional design was not an option, as this resulted in 32 choice scenarios. So, a fractional (factorial) design was used. This design resulted in a survey consisting of 16 choice scenarios. Each respondent was presented the full set of choice scenarios, meaning that he or she had to enter the probability for all 16 situations.

5. Data analyses

In total 116 respondents completely filled in the survey. Another 50 respondents started filling in the survey, but did not complete it. This was probably due to the many questions the respondents had to answer and the resulting long time it took to complete the questionnaire.

Table 3 shows the mean frequency and the corresponding standard deviation of the probabilistic intermediate activities. Fig. 2 shows the histogram of two probabilistic intermediate activities. The following observations can be made. The standard deviation associated with the probabilistic intermediate activities is rather large in comparison to their mean values. This relates to a large variation in the frequency of the probabilistic intermediate activities. In other words, there is a rather large difference in the performance of the probabilistic intermediate activities between each of the respondents. However, for most probabilistic intermediate activities the frequency is normally distributed, except for the activity *walk to mailbox*.

Table 4 shows the mean duration and frequency of the S-curve intermediate activities combined with the corresponding standard deviation. Fig. 3 illustrates the typical histograms of the frequency and duration of S-curve intermediate activities. These intermediate activities are also characterized by a rather large variation in both the frequency and duration. Furthermore, for most S-curve intermediate activities the distribution of the duration is left side askew. In the case of the S-curve intermediate activity *have a break* this relates to a rather strong preference for short breaks, assisted by the fact that the duration of an activity cannot be smaller than zero.

6. S-curve estimations

Using a stated choice experiment the utility of an activity cannot be observed directly. It is assumed to consist of structural component and a random term (similar to equation (1)), namely:

$$U_a = V_a + \varepsilon_a \tag{5}$$

where: U_a is utility of activity a, V_a is structural (or deterministic) utility of activity a, ε_a is error term (or random utility).

The structural utility V_a can be expressed as:

$$V_{a,ijk} = C_a + x_{a,i} + y_{a,j} + z_{a,k} \tag{6}$$

where: $x_{a,i}$ is type-of-day effect of activity a for level I, $y_{a,j}$ is type-of-activity effect of activity a for level j, $z_{a,k}$ is time effect of activity a for level k, C_a is constant utility in null situation.

The variable V_{context} can be expressed as:

$$V_{\text{context}} = x_a + y_a \tag{7}$$

where x_a is type-of-day effect of activity a, y_a is type-of-activity effect of activity a.

The null situation relates to the situation where the utility of an activity is not limited by the type-of-day effect, type-of-activity effect and the time effect. The first level of the three attributes (i.e. x_0, y_0 and z_0) corresponds to the null situation; the contribution of these levels to the overall utility is set to zero. The null situation leads to the maximum utility represented by the constant utility (C_a). This is the utility compared to the situation where the activity is not performed by an individual; the utility for not performing an activity is assumed to be zero.

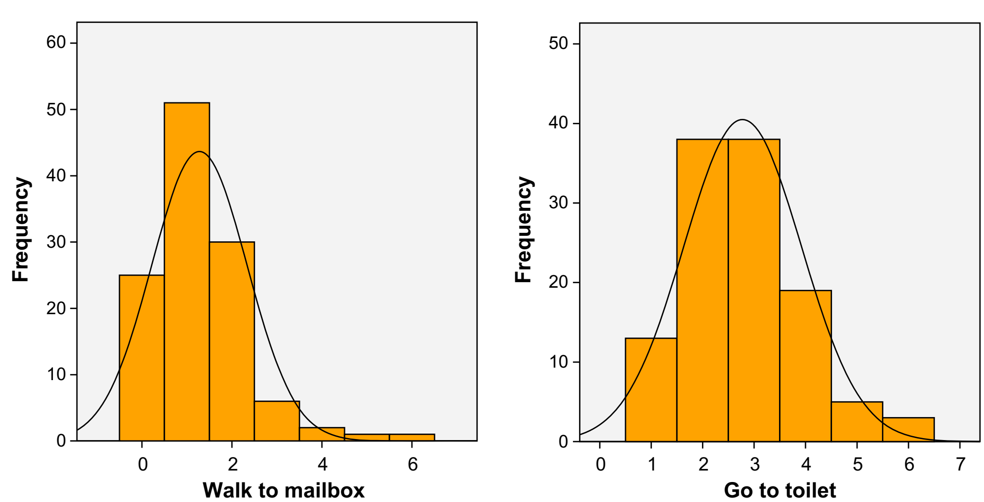

Fig. 2. Histograms of the frequency of probabilistic intermediate activities walk to mailbox and go to toilet.

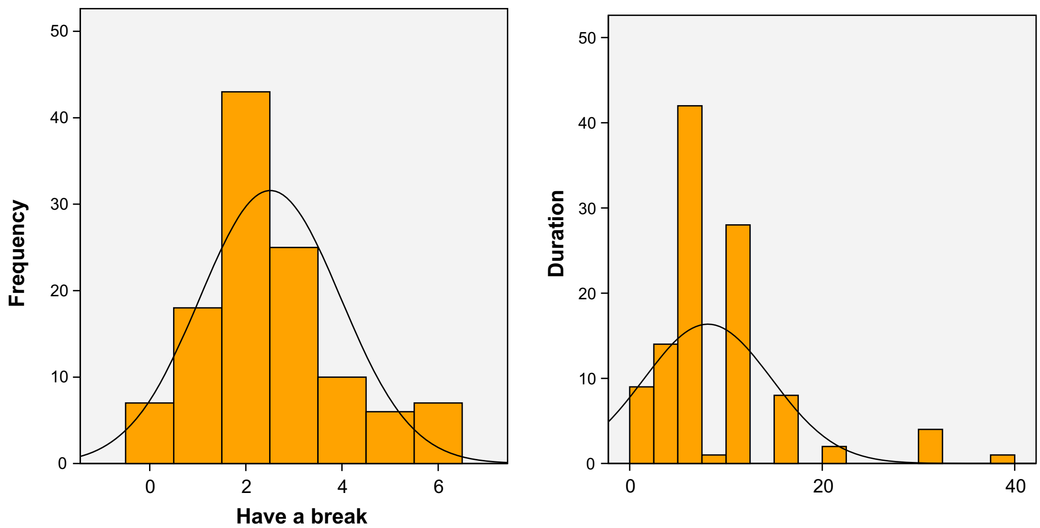

Fig. 3. Histograms of the frequency (left) and duration (right) of the S-curve intermediate activity have a break.

The probabilities entered by the respondents for each activity were used to estimate the coefficients of the type-of-day effect ($x_{a,i}$), type-of-activity effect ($y_{a,j}$) and time effect ($z_{a,k}$) attribute levels of equation (6). The coefficients were estimated using a standard multinomial logistic (MNL) model using dummy variables. These values were estimated per activity and per group of respondents belonging to a certain frequency interval.

The estimated values for the type-of-day effect ($x_{a,i}$) and type-of-activity effect ($y_{a,j}$) attribute levels represent the values of the context of the day variable (V_{context}) of function 2. The calculation of V_{context} is relatively straightforward. Almost all coefficients are found significant with a P-value <0.05. The time effect variable ($z_{a,k}$) is more easily analyzed when plotting the utility as a function of time. The outcomes of these analyses are presented in the next section.

6.1. Time effect analyses

The coefficients for the intermediate activity *have lunch*, *get a drink* and *have a break* results in a shape of the S-curve as expected. In Fig. 4 the *have a lunch* utility is presented as a function of time; the rightmost data point relates to the null situation. However, the coefficients of the activity *sport* resulted in an S-curve with a totally unexpected shape (see Fig. 5). Instead of an increasing utility with time, the utility decreases. As explained, for activities with a frequency of 1 the time levels represent the time elapsed since the start of the working day. These time effect attribute levels can be translated to real clock times. If we assume that an individual starts working around 8:30, the first level with a value of 3½ means 12:00, the second level being 4 means 12:30, etc. This means that for the S-curve intermediate activity *sport* the probability that an individual engages in this activity around 12:00 is relatively high. However, the later it gets the less likely it becomes that he will perform this intermediate activity. The most plausible reason for this is that the respondents weighted the probability of performing this intermediate activity on basis of the clock time and not on the time elapsed since the start of his working day. Apparently, the occurrence of this activity is strongly influenced by a clock time effect time, which is not taken into account in this model.

Each set of estimated coefficients of the time effect attribute levels lead to true S-curve shapes. However, the estimated coefficients for the intermediate activity *smoke* show an unexpected shape of the S-curve (see Fig. 6). The utility of the $z_{a,2}$ attribute level in the situation that the intermediate activity is not prior performed lies below the utility of the $z_{a,1}$ attribute level. An explanation for the unexpected drop in the S-curve can be found by again taking the corresponding clock times into account. The $z_{a,2}$ attribute level relates to a clock time of approximately 11:30. This is just before when most people will have lunch. Evidently, smokers do not find it worthwhile to smoke just before they have lunch; they will postpone the intermediate activity and combine it with going away for lunch. This leads to a lower utility for the intermediate activity around lunch time as seen in Fig. 6. Again, in this situation the behavior of people is strongly influenced by a clock time effect.

7. Results

In Table 1 we presented our assumption on appropriate prediction methods for intermediate activities based on their characteristics. In the following sections we present our results with regard to these assumptions and we provide the formula for prediction of intermediate activities by office occupants.

7.1. Prediction method: probability

In Section 6 we concluded that the activity ‘Sport’ and the activity ‘Smoke’ cannot be represented by the S-curve prediction method. Therefore we suggest to use a normal distribution for occurrence prediction of these activities. The Mean and Standard deviation can be calculated from the experiment data (Table 5).

The probabilistic intermediate activities are scheduled as follows. First, the number of times an employee performs one of

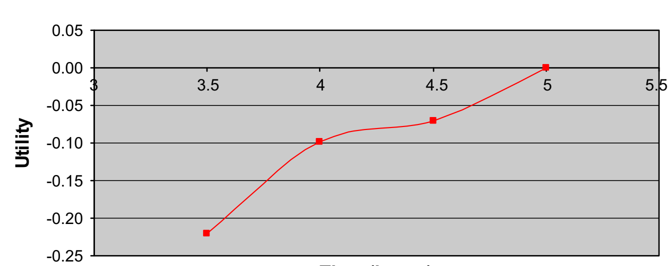

Fig. 4. S-curve based on the estimated coefficients of the time effect attribute levels (i.e. hours passed since start of working day) for intermediate activity *have lunch*.

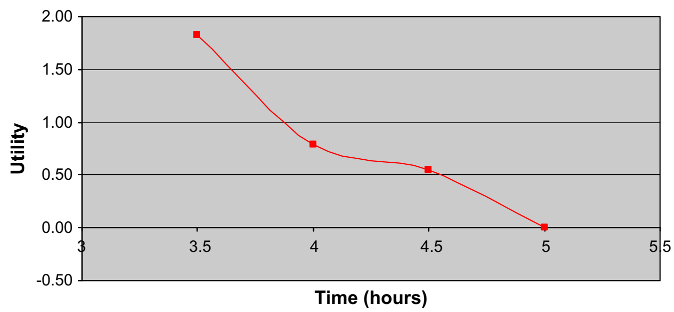

Fig. 5. S-curve based on the estimated coefficients of the time effect attribute levels (i.e. hours passed since start of working day) for intermediate activity *sport*.

these probabilistic intermediate activities during a working day are drawn based on the Mean and Standard deviation values. Next, each of the occurrences of this intermediate activity is scheduled. The start times of the occurrences are randomly spread over the duration of the workday, while taking into account a minimum time-interval between each of the occurrences. The minimum time-interval is used to prevent two or more occurrences of an intermediate activity following each other too close in time, for example within 5 min. For the first occurrence of an intermediate activity the whole working day is available as timeslot for drawing the start time; the start time is drawn somewhere between the start time and end time of the working day. While for each of the following occurrences the number of available time slots increases, the size of the available time slots decreases. The time slots get scattered of the working day; making it more difficult to draw a suitable start time. It can even occur that it is not possible to schedule all occurrences; remaining occurrences are discarded.

7.2. Prediction method: S-curve

Depending on the frequency entered by the respondent he or she was assigned to one of the following intervals: 1, 2–3 or 4-and-more occurrences of the intermediate activity per day. Table 6 shows the distribution of the respondents over the different frequency intervals as entered by the respondents.

Table 6 shows the range <min, max> of the context of the day variable ($V_{context}$) which is based on the estimated values for the type-of-day effect ($x_{a,i}$) and type-of-activity effect ($y_{a,j}$) attribute levels. The estimated coefficients of the time effect were used to fit the S-curve with as end result the values of the α and β parameters and the values of the V_{max} and V_{min} variables of equation (2) per S-curve intermediate activity (see Table 6). The process of curve fitting involves determining the values of the parameters and

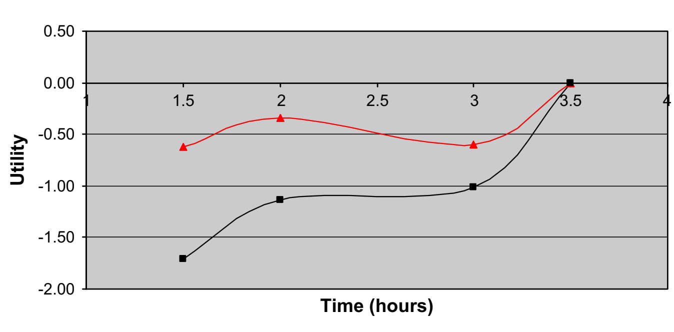

Fig. 6. Estimated coefficients of time effect attribute levels (i.e. hours passed since last activity occurrence) for intermediate activity *smoke*.

Table 5
Probability Mean and Standard deviation.

Intermediate activity	Frequency	
	Mean	Standard deviation
Go to toilet	2.78	1.14
Receive unexpected visitor	2.20	2.00
Walk to mailbox	1.28	1.06
Walk to printer	3.96	1.76
Sport (during workday)	0.82	0.39
Smoke (not at workplace)	2.22	1.64

variables in such a way that the S-curve goes in a most optimal way through the points of the estimated coefficients of the time effect attribute levels.

The random utility (ε_a) from equation (1) was not estimated in the experiment, but is applied to model the intermediate activity behavior more realistically (i.e. to add extra variation to the outcome of this model). It is assumed to be a double exponential distributed random value.

When the context of the day variable ($V_{context}$) is determined and the random utility (ε_a) is drawn the exact moment in time when $U_a = 0$ is can be calculated using equation (2) provided that $V_{max} > -V_{min}$.

$$t = -\frac{\ln\left(\frac{V_{max}}{-(V_{min} + V_{context} + C_a + \varepsilon_a)} - 1\right)}{\beta} + \alpha \qquad (9)$$

The calculated value t represents the time elapsed since the previous occurrence of the intermediate activity (i.e. the previous moment in time when $U_a = 0$) *or* it represents the time elapsed since the start of the working day if the activity has yet to occur.

For the S-curve method, the prediction now proceeds through a 6-step process.

1. For each activity draw a frequency interval using Table 6 through a Monte Carlo experiment.
2. From Table 7 select the S-curve parameter values for the first occurrence of the activity.
3. Calculate the time of first occurrence of the activity using equation (9).
4. For the next occurrence of the activity select the S-curve parameter values from Table 7.
5. Calculate the time of next occurrence of the activity using equation (9) and add this to the previous time of occurrence.
6. Repeat steps 4 and 6 until the end of the office hours is reached.

8. Discussion

The data found on 'go to toilet', 'smoke' and 'get a drink' concur with data from other resources. However, in many cases the way these data are collected and analyzed is unclear, and thus their reliability is unknown. The data presented here were collected and

Table 6
Number of respondents and probability per frequency interval.

S-curve intermediate activity	Frequency interval							
	0		1		2–3		4-and-more	
	N	%	*N*	%	*N*	%	*N*	%
Get a drink	–	0.0	6	5.2	44	37.9	66	56.9
Have a break	7	6.0	18	15.5	68	58.6	23	19.8
Have lunch	11	9.5	105	90.5	–	0.0	–	0.0

Table 7
Intermediate activity S-curve parameter values.

Intermediate activity	Freq	First/ next	α	β	V_{min}	V_{max}	$V_{context}$ <min, max>
Have lunch	1	n/a	81.540	0.018	−2.850	2.890	<−1.44, 0.13>
Get a drink	2–3	First	76.940	0.039	−2.810	2.820	<−1.13,
Get a drink	2–3	Next	107.510	0.014	−2.920	3.610	0.062>
Have a break	2–3	First	85.000	0.019	−3.150	3.400	<−1.16,
Have a break	2–3	Next	85.000	0.019	−3.260	3.520	0.045>
Get a drink	>4	First	−9.800	0.020	−3.920	4.300	<−1.61, 0.02>
Get a drink	>4	Next	131.000	0.025	−2.226	5.189	
Have a break	>4	First	35.100	0.040	−4.400	4.550	<−1.32, 0.20>
Have a break	>4	Next	3.000	0.0095	−4.400	5.850	

analyzed for Dutch office based organizations and are only applicable in this context. Although the values of the time effect attribute levels were estimated on a limited data set, they all significantly differ from zero and are statistical significant.

The probabilistic methods and the S-curve method can serve as estimates for any building performance simulation that requires detailed data on human behavior. In the presented research these methods were applied for office organizations, but application in other organization types is possible. Therefore the list of intermediate activities (as in Table 1) must be redefined and the experiment can be executed as described in this article to determine the mean values, and the parameter values for the S-curve. For the probabilistic method the values are independent of the context of the day. However for the S-curve values the context variables need also to be redefined according to the organization type.

Intermediate activities are part of the complete agenda of activities that an office worker will execute. Intermediate activities interrupt other activities typically found in (electronic) agenda such as: meeting, presentation, etc. These so-called skeleton activities depend on the role of a person in an organization. Such activities are usually described in function profiles by the human resource officer of the organization. Some organizations also maintain a time registration system on a person and project level. All these data sources combined can be used to generate a schedule of skeleton activities for each office worker on a daily basis for a certain period (e.g. a week). To get the full realistic agenda of human behavior these schedules must be updated with intermediate activities. Although theoretically a very detailed activity agenda can be generated, application always requires careful considerations. Predicting a single person's behavior is virtually impossible. The activity data only will provide insight on the average behavior of a human in building space including deviations from the mean values, but real behavior is always much more erratic.

The relevance of application of the presented estimated values and functions in building performance simulation depend on the level of accuracy that is appropriate at a certain design stage. More fine grained calculation methods require fine grained input data. As an example the SHOCC model from Bourgeois can import room occupancy data that are generated using the estimated values presented in this paper (see [13]). Sensitivity analyses studies are needed to research at which design stage and under which circumstances (building function and user type, building concept: passive/active systems, interaction between user and building, interaction between user and outdoor environment) accurate data on human behavior are necessary.

Application of human behavior models goes beyond building performance analysis and is also relevant in evacuation simulation, workplace assessment and facility utilization calculation. Evacuation simulation requires accurate data on the distribution of occupants in a building because this has a big impact on the evacuation time. Today usually an idealistic or random distribution is assumed which is of course far from reality. Accurate activity based models can predict occupant distribution at any time and/or generate worst case scenarios. workplace assessments are usually performed after the building was constructed, but can be executed in simulation models as well. Workplace assessment deals with psychological and physical aspects of the workplace. In all cases detailed data are required about the actual use of space. The capacity of facilities in a building such as elevators, stairs, coffee corners, meeting rooms, etc. are often estimated using rule-of-thumb or simple formulas based on empirical data. More accurate calculation of facility usage requires detailed data about the way the occupants actually use a building and its facilities. For these building evaluations, data on intermediate activities provide an important input.

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