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A context-aware method for building occupancy prediction

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ABSTRACT

In this paper a building occupancy prediction method is presented, which is based on the spatio-temporal analysis of historical data (occupancy modelling) and further relies heavily on current contextual information, being therefore suitable for providing real-time prediction. Two different algorithmic approaches are proposed, based on Markov models, revealing how context awareness adds the capability of rapidly adjusting to current conditions and capturing unexpected events, as opposed to capturing only typical occupancy fluctuation expected on a regular basis. Both proposed approaches are evaluated against accurate real-life data collected from a tertiary building, achieving notable results which outperform currently used methods.

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1. Introduction

Building energy consumption depends heavily on human presence and behaviour, since different sequences of activities and occupancy flows may result in different consumption patterns [1,2]. Occupant presence and behaviour in buildings have been shown to have large impact on heating, cooling and ventilation demand, energy consumption of lighting and appliances, and building controls [3]. Thus, human factor is very important in building energy management and real-time occupancy information offers great potential for assessing energy flexibility and maximizing energy efficiency [4].

Going one step forward, occupancy prediction can further facilitate building management planning, taking advantage of building thermal inertia in terms of proactive HVAC operation (preheating/cooling spaces and stop of operation prior to occupants departure) further allowing building operation against electricity market needs. Also, predictive strategies show better energy savings performance and even significantly better quality of service conditioning than reactive strategies [5].

Knowledge about occupancy prediction provides valuable information both on building and electricity grid level. On building level, real-time occupancy prediction could give information support for automated building energy management, real-time calculation of building energy flexibility and precise real-time energy efficient operation and planning. On grid level, such information could contribute to the reliable energy management of smart grids both on aggregator and distribution system operator level as well as to the participation of buildings in new energy business models of smart grids (demand response, dynamic pricing, demand side management, etc.).

As of today, various strategies and methods have been proposed to improve energy efficiency of commercial and home buildings that consider various environmental factors including occupancy. However, very little work has been published concerning building occupancy prediction. Occupancy prediction can be achieved by modelling long traces of occupancy data captured by a sensing system [6]. Probabilistic models (e.g. Markov Chain model, multivariate Gaussian model) would be suitable for such an application, since an occupant's future behaviour is influenced both by his/her past behaviour and current state and there are certain state transitions which are more likely to occur than others. Such models have been applied in literature [5–8] mostly for simulation purposes. However, existing methods do not consider current context (e.g. occupancy, spatial, temporal) and they usually include a random

Abbreviations: ARMA, autoregressive moving average; BCF, Bayesian combined forecasting; BCL, building component library; CD, closest distance; EERE, energy efficiency and renewable energy; HVAC, heating ventilation air conditioning; MC, Markov Chain; MRBS, Meeting Room Booking System; NREL, National Renewable Energy Laboratory; NRMSE, normalized round mean square error; PIR, passive infrared; PP, prediction parameterization; RMSE, round mean square error; SM, SEMI-Markov; SVM, support vector machine.

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factor making them less suitable for real-life applications. Furthermore, occupancy data are difficult to acquire and accurate ground truth values are rare as most buildings do not have sufficient infrastructure to properly sense people accurately throughout the building. Actually, inadequacy of data is commonly cited in literature as major obstacle for developing robust occupancy models.

Taking all the above into consideration, a context-aware occupancy prediction method is proposed, which is based on the spatio-temporal analysis of historical data (occupancy modelling) and current context information, and has the capability to provide short-term (few minutes ahead) or mid-term prediction (some hours ahead) per building occupancy zone. This method is suitable for real-time predictive control (e.g. for HVAC control replacing simple control based only on current occupancy). Two different approaches have been implemented. The first one is based on the Markov Chain model and is a modification of an existing method [5], while the second one is based on the Semi-Markov model and is a novel application for building occupancy modelling and prediction. For evaluation, occupancy data were collected from a tertiary building (a research institute) utilizing a robust and real-time occupancy extraction system, exploiting privacy preserving sensors [9,10], as well as PIR motion and acoustic sensors.

The contributions of this paper are as follows:

- Novel method for building occupancy prediction taking into account current context (occupancy, spatial, temporal, etc.).
- Application of the Semi-Markov modelling approach for building occupancy modelling and prediction.
- Creation of robust occupancy models based on accurate real-life data produced by a robust real-time occupancy extraction system (rather than data resulting from simulations), and reliable method evaluation based on experimentation performed under real-life rather than simulated conditions.

The paper is organized as follows: Section 2 describes the related work. Section 3 presents the proposed occupancy modelling and prediction framework, while Section 4 describes the experimental methodology for evaluation and analyses the results. Finally, Section 5 summarizes the paper and discusses future work.

2. Related work

Several works have been published that are relevant to building occupancy extraction and modelling, while the works that have been published on occupancy prediction are limited. In the past, the principle approach for modelling occupant presence in buildings was *diversity occupancy profiles* [11,12]. Although this approach offers an overall view of the average occupancy of the building, it is rather simple and fails to capture underlying relations between features and critical evidence affecting occupancy variations. Another popular approach is the use of *agent-based models* [8,13,14]. This method is unsuitable for real-time data fusion due to its high-degree of complexity. Agent based models also tend not to scale well to large buildings where the large numbers of agents, rooms and interactions lead to non-trivial solutions.

The authors in Ref. [8] propose a *multivariate Gaussian model* as well. This model is quite simple and serves as a coarse baseline model for other occupancy modelling and prediction approaches. However, its main drawback is that it causes a great deal of pacing behaviour and the distributions neither take into account previous behaviour nor accurately capture the usage of seldom used rooms. Both this model and the agent-based model described previously are mostly used for simulations and are useful for various off-line studies.

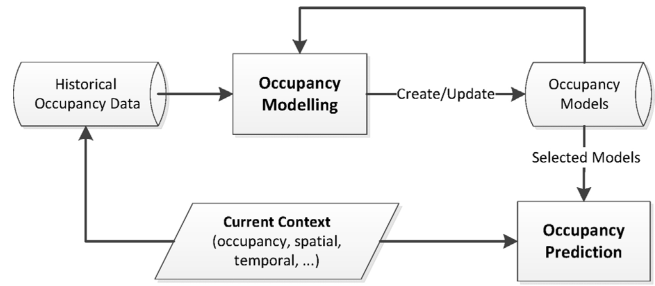

Fig. 1. Overview of the proposed framework.

A more accurate model utilizing a *Markov Chain* approach for a conditioning strategy is presented in Refs. [5,7]. The drawback of this approach is that it includes a random factor for state transitions making it more suitable for simulation and not real-life applications. Also, models are trained with a limited amount of real-life data (produced by a system [15] with only 80% reported accuracy) and prediction method evaluation is not so reliable since it is performed based on simulated and not real-life data. Another Markov Chain approach, which is used for building occupancy simulation, based on occupants' movements among spaces, is presented in Ref. [16].

The authors in Ref. [17] use a modified *Bayesian Combined Forecasting* (*BCF*) approach to forecast occupancy. This approach yields more accurate results than any of the component models, for short-term to medium-term forecasts. However, for horizons greater than about 60 min into the future, the method is no better than a simple historical daily average. Also, the collected datasets are based only on PIR sensors, which only detect motion instead of actual occupancy.

Finally, another useful modelling approach which seems to be suitable for occupancy is the *Semi-Markov* model. The Semi-Markov model is a generalization of the Markov Chain model differing mainly in the fact that the sojourn time at each state can follow any distribution and that a state cannot have a transit to itself. The Semi-Markov model has been used for reliability and survival analysis [18]. Also, the authors in Ref. [19] make use of semi-Markov processes to model the spatial and temporal movement of tourists. However, to our knowledge no work has been reported using the Semi-Markov model in the scope of building occupancy modelling and prediction.

3. Proposed framework

An overview of the overall proposed framework is provided in high level in Fig. 1. Historical occupancy data are derived by the continuous monitoring of the current context. The current context includes the current occupancy state as well as spatio-temporal aspects, such as the examined space, occupancy zones correlation, season, day of week, time of day, etc. These historical data are utilized by the occupancy modelling mechanism in order to create concrete occupancy models for the building areas examined. The created models are stored, in order to be retrieved later, and are updated on a regular basis. Taking into account the current context as well as the selected models among the available ones, occupancy prediction is then produced. The implemented algorithmic approach for occupancy modelling and prediction is presented in detail in the following sections.

All the variables used in the following sections are summarized in Table 1 for better readability.

Table 1
Summary of variables utilized throughout the paper.

Variable	Description	Variable	Description
a, c	Indeces	v	Number of time periods to be examined
M_i	Occupancy model	$\boldsymbol{T}(k)$	Transition matrix containing transition probabilities for after k timesteps
MI_{ij}	Instance j of model M_i	$\boldsymbol{T}_{MC}$	Transition matrix of the embedded Markov Chain
MP_{ij}	Parameter set of instance MI_{ij} of model M_i	$\boldsymbol{G}(k)$	Matrices containing the probability of the duration k in each state given the state subsequently occupied
w	Total number of model's instances	d_a	Duration of state $\boldsymbol{s}_a$
$\boldsymbol{s}_a$	Occupancy state a	d_{cur}	Duration of current state
$\boldsymbol{s}_{cur}$	Current occupancy state	$g_{ac}(k)$	Probability of staying at state $\boldsymbol{s}_a$ for k timesteps given that the next transition will be to state $\boldsymbol{s}_c$
occ_a	Occupancy of zone a	$n_{ac}(k)$	Number observed transitions from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$ with duration at $\boldsymbol{s}_a$ smaller than k timesteps
z	Total number of zones	n_{ac}	Total number of transitions from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$
u	Time period used for transition matrices defining their start and end time	$curCon$	Current context
t	Time period used for prediction	$Pred_{ij}$	Prediction made based on MI_{ij}
$\boldsymbol{T}_u$	Transition matrix for time period u	$predStateIndex$	The index of the predicted state ($\boldsymbol{s}_{predStateIndex}$)
$\boldsymbol{S}_u$	State matrix of $\boldsymbol{T}_u$	pm_a	The a-th row of matrix $\boldsymbol{PM}_u$
m	Total number of occupancy states	$pm_{a,c}$	The ak element of matrix $\boldsymbol{PM}_u$
$\boldsymbol{PM}_u$	Prediction matrix for time period u	$tr(d_{cur}+k)_a$	The a-th row of matrix $\boldsymbol{T}(d_{cur}+k)_u$
x	Total number of transition matrices	$tr(d_{cur}+k)_{a,c}$	The ac element of matrix $\boldsymbol{T}(d_{cur}+k)_u$
p_{ac}	Probability of moving from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$	$curSt$	The index of the current occupancy state ($\boldsymbol{s}_{curSt}$)
n_{ac}	Number of times a transition from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$ has been observed in the data set	$\underset{b}{\operatorname{argmax}}\{a\}$	The index b for which a is the maximum value
k	Timestep taking values from 1 to $TMTF$		

3.1. Occupancy modelling

Before proceeding into the creation of occupancy models it is necessary to study the building under consideration and its spatial structure in order to decide which areas will be modelled together and which separately. It is considered that a building comprises of one or more *occupancy zones*, defined as the smallest building spatial elements (floor, closed space, open space, sub-space, etc.) for which occupancy information is available. Occupancy of a zone can be represented by the exact number of occupants, a range based on the maximum expected value (defining categories such as empty, low, medium, nearly full and full), or a binary value (e.g. 0, 1) declaring just presence or absence of occupants.

Some occupancy zones which have high *functional* or *topological* correlation may be grouped together into *occupancy zone groups*. *Functional* correlation between two zones means that at specific time periods occupants regularly move from one zone to the other. For example, there is high correlation between an office and a kitchen if the occupants of the office usually leave during lunch time to eat at the kitchen. This results in having correlation also in terms of occupancy state, since the occupancy state of one zone affects the occupancy state of the other (e.g. in the above example low occupancy in the office during lunch time implies high occupancy in the kitchen). Furthermore, if $zone_1$ (e.g. office) and $zone_2$ (e.g. meeting room) are topologically connected through $zone_3$ (e.g. corridor), then an occupant should first make a transition from $zone_1$ to $zone_3$ and then from $zone_3$ to $zone_2$ in order to go from $zone_1$ to $zone_2$. In this case there is *topological* correlation. On the contrary, some occupancy zones (e.g. a meeting room) may operate independently from others, so they can comprise a group themselves and can be modelled separately. Thus, initially, occupancy zone groups should be determined for the building under consideration based on the functional and topological correlation of occupancy zones.

A separate model is created for each occupancy zone group. Furthermore, each model may have different instances, if necessary, based on *season* (autumn, winter, spring, summer, all, autumn-winter, etc.) and *typeOfDay* (weekday, weekend, Monday, ..., Sunday, all, Monday–Tuesday, etc.), since occupancy values may be highly dependent on these *temporal characteristics*. Thus, an occupancy model is defined as:

$$M_i = \{MI_{i1}, \ldots, MI_{iw}\} \tag{1}$$

where M_i is the occupancy model, MI_{ij} is the instance j of model M_i and w is the total number of model's instances.

Each particular model instance consists of one or more transition matrices, which determine the state changes within different slots of time, along with matrices containing their distinct states. Transition matrices have been utilized based on the intuition that an occupant's future behaviour is influenced both by his/her past behaviour and the current occupancy state, as well as that certain transitions among building areas are more likely to occur than others, taking also into account existing literature about occupancy modelling [5,7,16]. An occupancy *state* here is defined as a vector in which each element represents the occupancy in each zone of the examined occupancy zone group:

$$s = [occ_1, occ_2, \ldots, occ_z] \tag{2}$$

where occ_a is the occupancy of zone a, and z is the total number of zones. A *transition matrix* is a matrix where each element represents the probability of moving from one state to another:

$$\boldsymbol{T} = \begin{bmatrix} p_{11} & \cdots & p_{1m} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mm} \end{bmatrix} \tag{3}$$

where $\boldsymbol{T}$ is the transition matrix, m is the total number of states and p_{ac} is the probability of moving from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$.

Each transition matrix $\boldsymbol{T}$ is accompanied by a state matrix $\boldsymbol{S}$ which contains all the distinct occupancy states:

$$\boldsymbol{S} = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_m \end{bmatrix}, \tag{4}$$

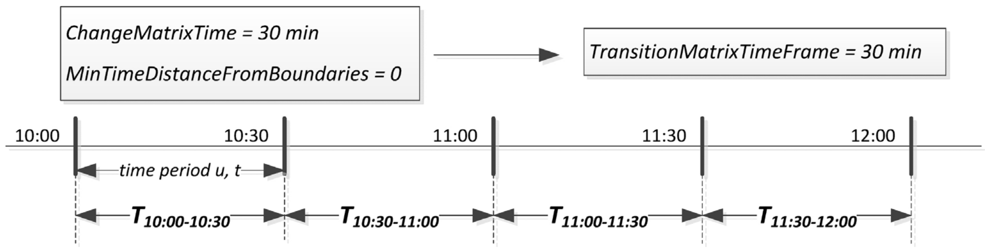

Fig. 2. Example of transition matrix parameters without overlapping.

where $\boldsymbol{s}_a$ is state a and m is the total number of states of matrix $\boldsymbol{T}$. Thus, a model instance is defined as:

$$MI_{ij} = \{\boldsymbol{T}_1, \boldsymbol{T}_2, \ldots, \boldsymbol{T}_x, \boldsymbol{S}_1, \boldsymbol{S}_2, \ldots, \boldsymbol{S}_x\} \tag{5}$$

where $\boldsymbol{T}_u$ is the transition matrix for time period u (as defined by $TMTF_j$), $\boldsymbol{S}_u$ is the state matrix of $\boldsymbol{T}_u$ and x is the total number of transition matrices. Time period u is actually the period which the historical data used to build the transition matrix concern. For example, $\boldsymbol{T}_{10:00–10:30}$ is the transition matrix which has created based on occupancy data between 10:00 and 10:30.

A particular model instance MI_{ij} is defined by some parameters, which are divided into general parameters and those who are related with transition matrices as explained below:

- General parameters
  - *ObservationTimestep* (*in s*)*:* it defines the sampling rate of occupancy values (i.e. per how many seconds occupancy is observed) and consequently the model instance's timestep. *ObservationTimestep* is based on the granularity of the utilized historical occupancy data and can be the same or higher depending on the desired occupancy prediction granularity. For example, if historical occupancy data are available per minute, *ObservationTimestep* can be equal to one or more minutes.
  - *OccupancyValueType*: it defines the type of the occupancy values.
    - exact number of occupants
    - occupancy range (empty, low, medium, full, etc.), where the number of ranges should also be defined, or
    - presence/absence.
- Transition Matrix parameters
  - *ChangeMatrixTime* (*in min*)*:* it defines per how many minutes a different transition matrix is used.
  - *MinTimeDistanceFromBoundaries* (*in min*): it defines the minimum additional time before and after the time limits determined by *ChangeMatrixTime* which eventually determines transition matrices start and end time. It is used for *overlapping* in order to smooth occupancy state transitions near time periods limits. If it is set to zero, no overlapping is considered.
  - *TransitionMatrixTimeFrame*: it defines the duration of the time period covered by each transition matrix. Its value is automatically determined by the values of *ChangeMatrixTime* and *MinTimeDistanceFromBoundaries* by the following equation:

$$\begin{aligned} &TransitionMatrixTimeFrame \\ &\quad = ChangeMatrixTime + 2 * MinTimeDistanceFromBoundaries \end{aligned} \tag{6}$$

Two examples for transition matrix parameters with and without overlapping are given in Figs. 2 and 3, respectively. In Fig. 2, a different transition matrix is defined per 30 min and the limits of each time period are the same with the start and end time of the respective matrix. For instance, for 10:00–10:30 the transition matrix used is $\boldsymbol{T}_{10:00–10:30}$. In Fig. 3, a different transition matrix is defined per 20 min and each transition matrix covers the respective time period as well as 10 min before and after that. For instance, for 10:00–10:20 the transition matrix used is $\boldsymbol{T}_{9:50–10:30}$ and there is 20 min overlapping between two successive matrices.

Model instance's parameters are included in the parameter set MP:

$$MP_{ij} = \{season_j, dayType, obsT_j, occValType_j, CMT_j, MTDB_j, TMTF_j\} \tag{7}$$

where MP_{ij} is the parameter set of instance MI_{ij} of model M_i; $season_j$ is the season of the model instance; $dayType_j$ is the type of day of the model instance; $obsT_j$ is the *ObservationTimestep* of the model instance; $occValType_j$ is the *OccupancyValueType* of the model instance; CMT_j is the *ChangeMatrixTime* of the model instance; $MTDB_j$ is the *MinTimeDistanceFromBoundaries* of the model instance; $TMTF_j$ is the *TransitionMatrixTimeFrame* of the model instance.

All the parameters utilized along with the respective variables are summarized in Table 2.

For the creation of transition matrices, two approaches have been implemented. The first one is based on the *Markov Chain* model, while the second one is based on the *Semi-Markov* model. The required *inputs* for both approaches are: the maximum expected number of occupants per occupancy zone and historical occupancy data. For each occupancy zone group, historical occupancy data should be available per zone for a number of days or months resulting from an occupancy extraction framework. For each zone occupancy values should be given per date and time based on a predefined observation timestep (e.g. per second or

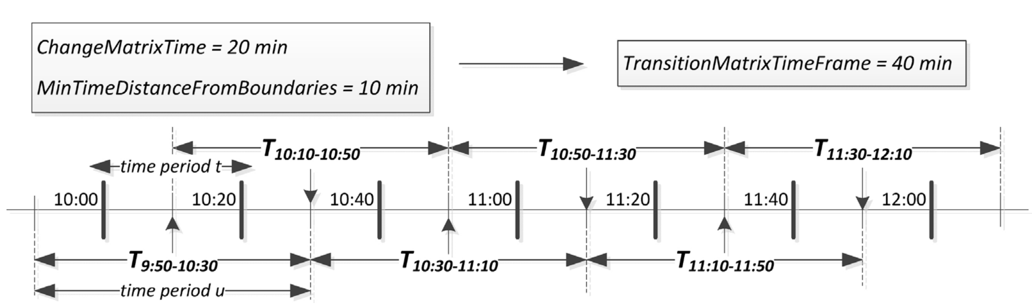

Fig. 3. Example of transition matrix parameters with overlapping.

Table 2
Summary of parameters and corresponding variables utilized.

Variable	Parameter	Description
Occupancy modelling		
General parameters		
$obsT_j$	*ObservationTimestep* (*in s*)	Model instance's timestep
$occValType_j$	*OccupancyValueType*	Type of occupancy values (exact number, occ. Range, presence/absence)
Transition Matrix parameters		
CMT_j	*ChangeMatrixTime* (*in min*)	Defines per how many minutes a different transition matrix is used
$MTDB_j$	MinTimeDistanceFromBoundaries (*in min*)	Minimum additional time before and after the time limits determined by *ChangeMatrixTime*
$TMTF_j$	*TransitionMatrixTimeFrame*	duration of the time period covered by each transition matrix
Temporal parameters		
$season_j$	*season*	Season of the model instance (e.g. winter, summer, autumn-winter, all)
$dayType_j$	*typeOfDay*	Type of day of the model instance (e.g. weekday, weekend, Monday)
Occupancy prediction		
PredictionFrequency	How often a new prediction is produced	
PredictionWindow	The time frame ahead current time which is covered by the prediction	

Inputs

- Maximum expected number of occupants per occupancy zone
- Historical occupancy data

Algorithmic Approach

- Use Markov Chain or Semi-Markov Model to create all the Transition Matrices ($\boldsymbol{T}_u$) containing probabilities for occupancy states transitions for each time period

Outputs

- Transition Matrices ($\boldsymbol{T}_u$) and corresponding State Matrices ($\boldsymbol{S}_u$) for each time period according to the parameter set MP

Fig. 4. Inputs, outputs and high-level algorithmic approach of the proposed Occupancy Modelling method.

minute). From the available historical occupancy data some days are used for training and some days are left out for testing purposes. The inputs, outputs and the general algorithmic approach in high level for creating a particular model instance are summarized below in Fig. 4, while the detailed approaches based on Markov and Semi-Markov model are presented in Sections 3.1.1 and 3.1.2 correspondingly.

3.1.1. Markov Chain model

The algorithmic approach for the creation of the transition matrix for each time period (defined according to model parameters) is based on Ref. [5] and is summarized in Fig. 5.

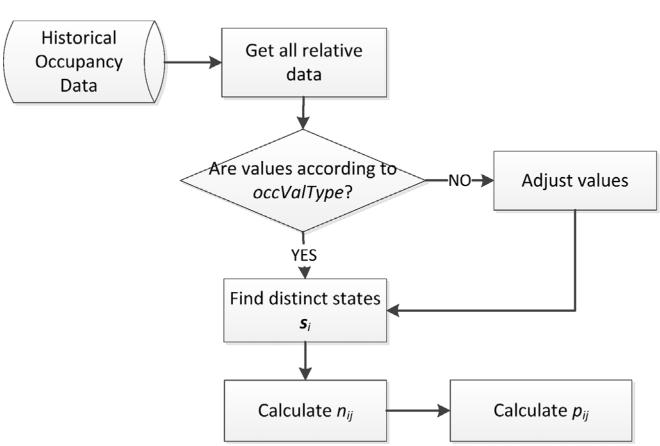

Fig. 5. Algorithmic approach to create a transition matrix for a specific time period based on MC model.

In the first step the occupancy data concerning the examined time period (e.g. 10:00–10:30) are selected from the historical occupancy data repository. Then, if the values are not available in the desired form (*OccupancyValueType*), they are translated into it if possible (e.g. if occupancy is extracted in ranges, prediction cannot provide the exact number of occupants). In the next steps the distinct occupancy states are found and the number of transitions from state to state is calculated based on selected occupancy data. Finally, the probabilities of transitions between states are calculated according to the following equation:

$$pac = \frac{ni_j}{\sum_{u=1}^{m} n_{iu}} \tag{8}$$

where p_{ac} is the probability of moving from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$, n_{ac} is the number of times a transition from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$ has been observed in the data set and m is the total number of states.

3.1.2. Semi-Markov model

The implemented algorithmic approach is based on the mathematical approach of [20], which propose an algorithm for the solution of the DTHSMP (Discrete Time Homogeneous Semi-Markov Process). In particular, the authors provide an algorithm for the calculation of the semi-Markov transition probabilities, as follows:

$$\boldsymbol{T}(k) = f(m, v, \boldsymbol{T}_{MC}, \boldsymbol{G}(k)) \tag{9}$$

where k is the timestep taking values from 1 to *TMTF*; $\boldsymbol{T}(k)$ is the transition matrix containing the probabilities of transitioning from one state to another after k timesteps; m is the total number of states; v is the number of time periods to be examined; $\boldsymbol{T}_{MC}$ is the transition matrix of the embedded Markov Chain; $\boldsymbol{G}(k)$ for $k = 1, \ldots,$ *TMTF* are matrices containing the probability of the duration k in each state given the state subsequently occupied.

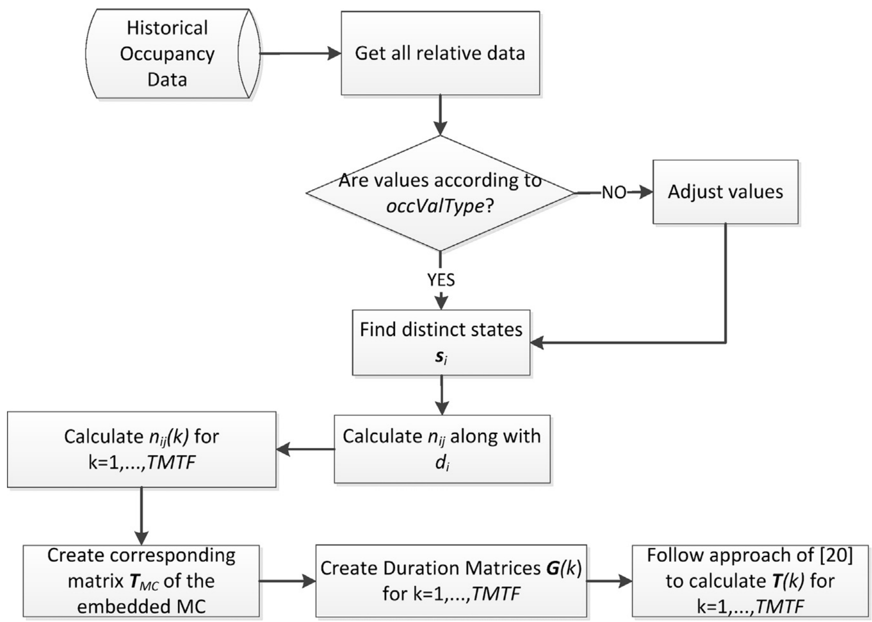

Fig. 6. Algorithmic approach to create transition matrices for a specific time period based on SM model.

A basic difference from the Markov Chain model approach is that for a specific time period there is not only one transition matrix but there are as many matrices as the *TMTF* which are defined by $\boldsymbol{T}(k)$.

The implemented algorithmic approach for the creation of the transition matrices ($\boldsymbol{T}(k)$) for each time period (defined according to the model parameters) is summarized in Fig. 6. In the first step the occupancy data concerning the examined time period (e.g. 10:00–10:30) are selected from the historical occupancy data repository. Then, if values are not available in the desired form (*OccupancyValueType*), they are translated accordingly, if possible, and the distinct occupancy states are identified. In the next step the number of transitions from state to state is calculated along with state durations (d_a). Also, the number of transitions with specific duration is calculated for all possible duration values (from 1 to *TMTF*). Then, the corresponding transition matrix $\boldsymbol{T}_{MC}$ of the embedded Markov Chain is created based on equation 8, and duration matrices $\boldsymbol{G}(k)$ for k = 1,. . ., *TMTF* are calculated based on the equation:

$$g_{ac}(k) = \frac{n_{ac}(k)}{n_{ac}} \quad (10)$$

where $g_{ac}(k)$ is the probability of staying at state $\boldsymbol{s}_a$ for k timesteps given that the next transition will be to state $\boldsymbol{s}_c$; $n_{ac}(k)$ is the number of times a transition from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$ has been observed in the historical data set with duration at $\boldsymbol{s}_a$ smaller than k timesteps; n_{ac} is the total number of transitions from state $\boldsymbol{s}_a$ to $\boldsymbol{s}_c$.

Finally, the Semi-Markov evolution equations are solved based on the algorithm of [20] and the Semi-Markov transition probabilities are calculated resulting to the creation of the respective transition matrices ($\boldsymbol{T}(k)$).

3.1.3. Model initialization and update

Occupancy model for each occupancy zone group is built based only on real historical data. Then, if a real-time occupancy extraction framework is available continuously producing new data, the model is automatically updated on a regular basis (e.g. at the end of each day, week, month). The update function assigns weights to the occupancy data based on an F-distribution (Fisher), so that very old data are discarded and more weight is given to recent data, in order to better depict current occupancy patterns and address any changes (e.g. new personnel added).

Otherwise, when no real occupancy data are available for the occupancy zone group under consideration (e.g. before installing an occupancy extraction framework), model initialization can be performed based on publicly available *open reference occupancy models* (e.g. by the BCL of NREL,[1] Autodesk Vasari,[2] EERE[3] or by ongoing European related projects[4]). Open reference occupancy models are typical models containing occupancy distribution for major types of tertiary buildings/spaces, such as offices, hotels, hospitals, restaurants, etc.

3.2. Occupancy prediction

Combining the created model described in the previous chapter with current context information (e.g. occupancy, spatial, temporal, etc.), the proposed occupancy prediction mechanism provides either short-term (few minutes after real-time) or mid-term (after some hours from current time) prediction for each zone of the examined occupancy zone group. The implemented mechanism runs in a continuous and automatic way providing occupancy prediction from current time ahead per *ObservationTimestep* based on the specification of the following parameters: *PredictionFrequency* (how often a new prediction is produced) and *PredictionWindow* (the time frame ahead current time which is covered by the prediction). Values of the above prediction parameters are defined based on the application. An example for *PredictionFrequency* = 15 min, *PredictionWindow* = 30 min and *ObservationTimestep* = 1 min, and for current time from 10:00 to 10:30 is provided in Table 3.

Two algorithmic approaches have been implemented based on the Markov Chain and Semi-Markov model described in the previous section. The necessary input for both approaches is a particular occupancy model instance (MI_{ij}), which is created as analyzed in

[1] https://bcl.nrel.gov/.
[2] Autodesk 360 Energy Analysis – Vasari (http://autodeskvasari.com).
[3] http://www.eere.energy.gov/.
[4] e.g. Adapt4EE – Occupant Aware, Intelligent and Adaptive Enterprises (2011: FP7 ICT – STREP), http://www.adapt4ee.eu.

Inputs

- Particular model instance (MI_{ij}) to be used
- Current context (*curCon*) at each timestep ($obsT_j$)

Algorithmic Approach

- At each step (defined by *PredictionFrequency*)
  - For each time period (defined by CMT_j) and until covering *PredictionWindow*
    - Use the Prediction Algorithm based on Markov Chain or Semi-Markov Model to produce predicted occupancy state per *obsTj*

Outputs

- At each step (defined by *PredictionFrequency*)
  - Predicted distinct occupancy states $\boldsymbol{s}_a$ (occupancy per zone) depicting only changes from *currentTime* until *currentTime+PredictionWindow*

Fig. 7. Inputs, outputs and high-level algorithmic approach of the proposed Occupancy Prediction method.

Section 3.1, as well as a framework providing in every timestep the current context. Thus, prediction can be written generally as a function H:

$$Pred_{ij} = \mathrm{H}(MI_{ij}, curCon) \tag{11}$$

where MI_{ij} is the instance j of the occupancy model M_i to be used, *curCon* is the current context and $Pred_{ij}$ is the prediction made based on MI_{ij}.

The model instance to be used should be fully specified defining all necessary parameters of the parameter set *MP*. Parameterization may have an important impact on the final outcome, thus during training period optimal values selection should be performed.

As far as the outputs are concerned, the prediction mechanism at each step, as defined by *PredictionFrequency*, produces the predicted occupancy per zone (in the form of the defined $occValType_j$) for all the zones of the examined occupancy zone group, depicting only changes, from current time until covering the prediction window. The predicted values are calculated per a specified timestep which is the same as the defined model instance's observation timestep ($obsT_j$).

The inputs, outputs and the general algorithmic approach in high level are summarized in Fig. 7. The detailed proposed method both for the Markov Chain and the Semi-Markov model is analyzed in the following Sections 3.2.1 and 3.2.2, respectively.

3.2.1. Markov Chain

The proposed occupancy prediction algorithmic approach based on the Markov Chain model for each time period *t* (as defined by CMT_j – see also Figs. 2 and 3) of a single prediction step (as defined by *PredictionFrequency*) is presented in high level in Fig. 8. Initially, the state matrix ($\boldsymbol{S}_u$) used for the respective time period *t* is retrieved from the model instance (MI_{ij}). Then, since only observed states are considered for the creation of the state matrix, and consequently for the transition matrix, and not all possible states, it is checked whether the current occupancy state ($\boldsymbol{s}_{cur}$) exists between distinct states. If it does not exist, its distance from each observed distinct state is calculated according to the Closest Distance (CD) algorithm [5] and the state with the smallest distance is chosen instead. If there are more than one states with the minimum distance, the one with the smaller occupancy differences per zone is selected.

Following, the appropriate Transition Matrix ($\boldsymbol{T}_u$) is retrieved from the model instance (i.e. the one corresponding to the examined time period *t*). Then, prediction is calculated per timestep ($obsT_j$) from current time until the end of the respective time period or until the end of the prediction time frame (if it ends earlier than the examined time period). The predicted occupancy state for y timesteps after current time is calculated based on the probabilities of the Transition Matrix ($\boldsymbol{T}_u$) raised on the y-th power, which is called Prediction Matrix ($\boldsymbol{PM}_u$):

$$\boldsymbol{PM}_u = \boldsymbol{T}_u^y \tag{12}$$

Starting from the current occupancy state, the predicted state is considered as the one with the highest transition probability in the Prediction Matrix based on the equation:

$$predStateIndex = \mathrm{argmax}_b\{pm_{curSt,b}\} \tag{13}$$

where *predStateIndex* is the index of the predicted state ($\boldsymbol{s}_{predStateIndex}$); pm_a is the a-th row of matrix $\boldsymbol{PM}_u$; $pm_{a,c}$ is the ac element of matrix $\boldsymbol{PM}_u$; *curSt* is the index of the current occupancy state ($\boldsymbol{s}_{curSt}$); $\mathrm{argmax}_b\ \{pm_{curSt,b}\}$ is the index b for which $pm_{curSt,b}$ is the maximum value of row pm_{curSt}.

Finally, at the end of the examined time period (when prediction for all intermediate steps has been calculated) and as long as it is not the last one, current occupancy state is set equal to the last predicted state and current time is set equal to the respective prediction time. The same procedure is repeated for the next time period.

3.2.2. Semi-Markov

The occupancy prediction algorithmic approach based on the Semi-Markov model is presented in high level in Fig. 9. As it seems, it is similar to the Markov Chain approach. A main difference is that at the start of each time period *t* the duration of current occupancy state (d_{cur}) is also calculated based on the previous occupancy data. Also, for the calculation of the predicted state for each timestep *k* inside a time period, the respective Semi-Markov Transition Matrix ($\boldsymbol{T}(d_{cur}+k)_u$) is used (i.e. the one concerning the corresponding duration) instead the Prediction Matrix ($\boldsymbol{PM}_u$). For example, if current occupancy state duration is equal to 5 timesteps (e.g. 5 min), the Semi-Markov Transition Matrix used to calculate prediction after 10 timesteps (e.g. 10 min) from current time will be $\boldsymbol{T}(15)$. The predicted state index is calculated as follows:

$$predStateIndex = \mathrm{argmax}_b\{tr(d_{cur}+k)_{curSt,b}\} \tag{14}$$

where *predStateIndex* is the index of the predicted state ($\boldsymbol{s}_{predStateIndex}$); *k* is the timestep for which prediction is made;

Table 3
Example for PredictionFrequency = 15 min, PredictionWindow = 30 min and ObservationTimestep = 1 min.

Current time	Prediction time frame	Prediction times
10:00	10:00–10:30	10:01, 10:02, . . ., 10:30
10:15	10:15–10:45	10:16, 10:17, . . ., 10:45
10:30	10:30–11:00	10:31, 10:32, . . ., 11:00

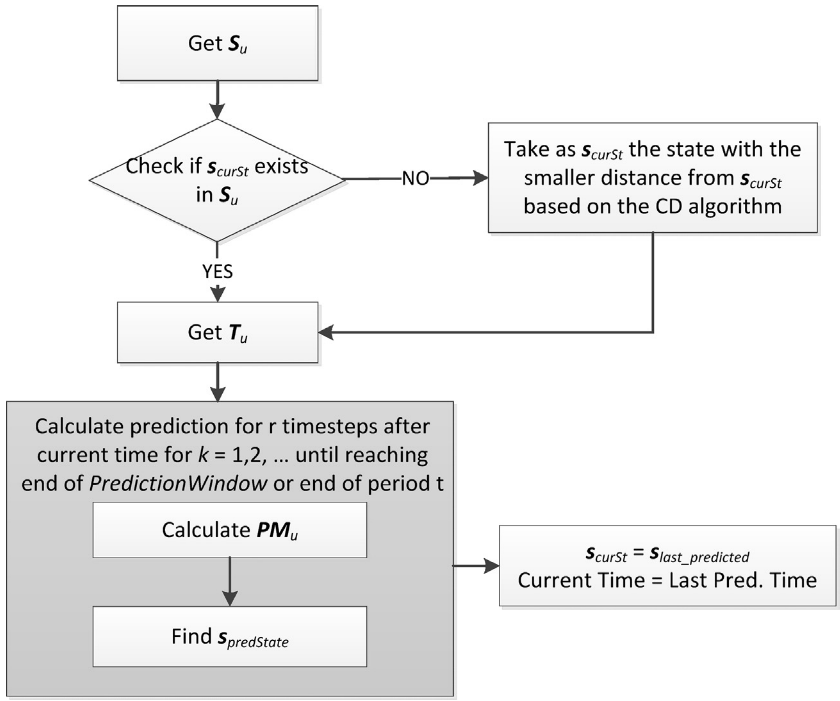

Fig. 8. Algorithmic prediction approach based on MC model for a specific time period of a single step.

$tr(d_{cur}+k)_a$ is the a-th row of matrix $\boldsymbol{T}(d_{cur}+k)_u$; $tr(d_{cur}+k)_{a,c}$ is the ac element of matrix $\boldsymbol{T}(d_{cur}+k)_u$; *curSt* is the index of the current occupancy state ($\boldsymbol{s}_{curSt}$); $\arg\max_b\{tr(d_{cur}+k)_{curSt,b}\}$ is the index b for which $tr(d_{cur}+k)_{curSt,b}$ is the maximum value of row $tr(d_{cur}+k)_{curSt}$.

4. Experimental results

In this section results are presented concerning the experiments performed in order to validate and evaluate the proposed occupancy modelling and prediction framework under different

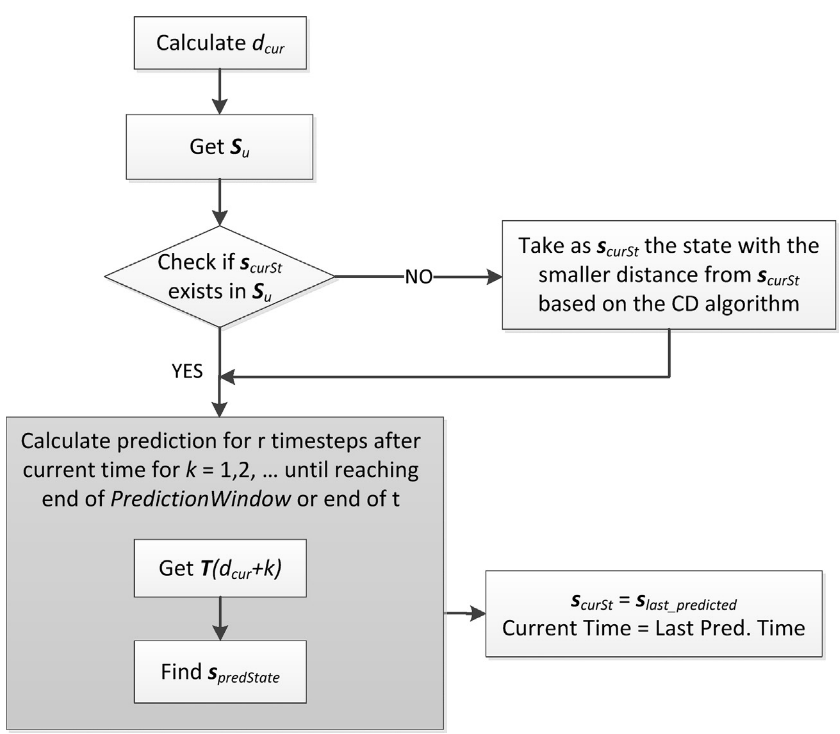

Fig. 9. Algorithmic prediction approach based on SM model for a specific time period of a single step.

Fig. 10. Examined spaces of the research institute (a) Office, (b) Kitchen and (c) Rest Area.

circumstances testing various scenarios. Experiments have been performed based on real-life occupancy data extracted from a research institute for three different types of spaces (Office, Kitchen, Rest Area), shown in Fig. 10, in order to cover a range of tertiary and commercial building spaces:

- *Office*: The examined office is a closed-space developers office with two entrances/exits, which includes 10 workplaces divided in cubicles following a not so typical working hours schedule. This space is an indicative case of a flexible office in the sense that although occupants normally follow a typical timetable, arrival and departure times often present high diversity among different days. A lunch break may occur as well either on standard hours or not. Two occupancy zone groups have been examined for this space: in the first case the whole office is considered as one zone, while in the second case the office is divided into 3 zones[5] (*Office_NE*, *Office_SW_01* and *Office_SW_02*), as depicted in Fig. 11a, based on the space layout and the lighting/air-conditioning zones.
- *Kitchen*: The examined kitchen is used by the occupants of the research institute throughout the day and can accommodate up to 40 people. This space is an indicative case of an eating area which follows a systematic occupancy pattern, as the highest occupancy density is usually observed at meal times while during the rest hours there is diverse occupancy for short periods. Two occupancy zone groups have been examined also for this space: in the first case the whole kitchen is considered as one zone, while in the second case the kitchen is divided into 2 zones (*Kitchen_Sink* and *Kitchen_Tables*), as depicted in Fig. 11b, based on the space layout and the existence of two different sub-spaces with different lighting zone, air condition (HVAC), operation and occupancy pattern. In *Kitchen_Sink* occupants stay for a short time either for using an appliance or for dish washing, while in *Kitchen_Tables* occupants usually eat during lunch and stay for longer periods of time.
- *Rest Area:* The examined rest area is an open space interconnected with the main corridor of the floor, where there are two tables, which are used for short meetings, a couch and a vending machine. This space is an indicative case of an open-space rest and meeting area, hosting unofficial meetings and breaks which last from a few minutes to some hours following an occupancy pattern which is characterized by high diversity. It is typical for this area to be occupied for short time-periods, while it may also be unoccupied for relatively long periods. One occupancy zone is only considered here, as depicted in Fig. 11c.

For the first two spaces (Office, Kitchen) the exact number of occupants was extracted based on installed depth-image cameras using the real-time and privacy-preserving occupancy extraction system described in Refs. [9,10]. This system is quite robust, reliable and accurate providing results very close to ground truth (95% accuracy).

For the third space (Rest Area) only occupancy presence/absence was extracted based on an acoustic sensor and a PIR sensor (motion detector), covering the space, both for privacy reasons (an area with many external visitors) and for testing a low-cost and simple scenario. The output of the PIR motion sensor is binary. When movement is detected, an activation event is sent by the sensor. A deactivation event is sent after a 3-s time period of no movement detection. Based on these simple events as well as on the output of the acoustic sensor, occupancy detection was performed.

4.1. Experimental methodology

In the current section the experimental methodology followed for the evaluation of the presented framework is described along with the evaluation metric used. For all the occupancy zone groups, both prediction methods have been tested (Markov Chain, Semi-Markov). Based on the available occupancy data, various models have been created for each examined occupancy zone group using various parameterizations. Due to space limitations, only the

[5] *Office_Central* zone is not used for prediction as it operates as a corridor with only instantaneous passages.

Fig. 11. Division of spaces into occupancy zones (a) Office, (b) Kitchen and (c) Rest Area.

Table 4
Transition matrix parameters for tested models.

Transition matrix parameters	Model			
	MC 30-0 (min)	MC 20-10 (min)	SM 5-0 (min)	SM 5-5 (min)
ChangeMatrixTime	30	20	5	5
MinTimeDistanceFromBoundaries	0	10	0	5
TransitionMatrixTimeFrame	30	40	5	15

results from the two best models for each case are presented, which are the ones shown in Table 4.

This is actually the procedure that needs to be followed in practice in order to define model parameters for an examined occupancy zone group in a real building. Initially, various models are created based on at least 1–2 weeks of historical training occupancy data. Then, the models are evaluated (against a set of days which have been left out for testing) and the optimal one is finally selected for occupancy prediction.

For the experiments described the following parameter values have been used: *season* = *Winter*, *dayType* = *Weekday*, *obsT* = 60 s, *occValType* = *occupancy range* (Table 5) for Office and Kitchen, and *occValType* = *presence/absence* (Table 6) for Rest Area.

Three cases are examined for each occupancy zone group with respect to the *PredictionFrequency* and *PredictionWindow*, as described in Table 7. These cases have been selected in order to cover some indicative real-life scenarios where occupancy prediction could be used. PP1 represents a mid-term prediction concerning 8 h ahead (updated every 8 h) which can be used for operational and energy resources planning. PP1 is not very context-aware since it takes into account current context information only 1–3 times a day (depending on start and end time). PP2 represents a short-term prediction (1 h ahead, updated every half-hour) which can be used for building automation (e.g. energy-efficiency mode). PP3 stands for an even more short-term prediction (half-hour ahead, updated every 15 min) which can be utilized for demand response programmes or for building automation as well. PP3 is highly context-aware since it looks into current context every 15 min. Finally, PP4 is more short-term than PP3 providing prediction every 15 min for 15 min ahead. This could also be used for demand response or real-time predictive control.

A part of the available dataset is used for models creation (training), while the rest is left out for prediction evaluation (testing). At each step (time period), which is defined by the examined PP, the current occupancy state is obtained by the respective occupancy value of the examined testing day. Based on the current occupancy state and the examined model a prediction is made and is then compared against the corresponding testing data (actual occupancy), which are considered as ground truth. In particular, for prediction evaluation, based on relevant literature, the total average NRMSE

Table 5
Explanation of the occupancy value type used for Office and Kitchen.

Occ. value (range number)	Description	Percentage (%)
0	Empty	0
1	Low	(0, 25]
2	Medium	(25, 50]
3	Nearly Full	(50, 75]
4	Full	(75, 100]

Table 6
Explanation of the occupancy value type used for Rest Area.

Occ. value	Description
0	Absence
1	Presence

Table 7
Prediction parameters values used in experiments.

Parameter	Prediction parameterization (PP)			
	PP1 (h)	PP2 (min)	PP3 (min)	PP4 (min)
PredictionWindow	8	60	30	15
PredictionFrequency	8	30	15	15

Table 8
Total average NRMSE for office.

Method	3 occupancy zones Prediction parameterization (PP)				1 occupancy zone Prediction parameterization (PP)			
	PP1 (%)	PP2 (%)	PP3 (%)	PP4 (%)	PP1 (%)	PP2 (%)	PP3 (%)	PP4 (%)
Prediction (MC 30-0)	**22.36**	18.25	15.33	12.02	11.37	8.21	6.70	4.86
Prediction (MC 20-10)	26.74	**17.49**	**14.78**	11.88	**11.17**	**7.88**	**6.45**	**4.69**
Prediction (SM 5-0)	26.97	19.59	15.81	**11.87**	15.88	9.96	7.19	4.77
Prediction (SM 5-5)	25.97	18.78	15.73	12.05	20.42	11.62	7.80	4.93
Historical average	26.74	21.86	20.53	19.28	20.48	16.20	14.64	13.56
Open reference model	30.88	27.65	26.07	24.57	27.35	22.50	20.91	19.69

(normalized root-mean-square error) is calculated for each prediction parameterization and for each model as follows:

$$Total\,Average\,NRMSE = \frac{\sum_{i=1}^{TestD} AverageNRMSE\_day_i}{TestD} \tag{15}$$

where *testD* is the total number of testing days.

$$Average\,NRMSE\_day_i = \frac{\sum_{t=1}^{tp} NRMSE\_period_t}{tp} \tag{16}$$

where $AverageNRMSE\_day_i$ is the average NRMSE of the testing day i; z is the total number of zones contained in the examined occupancy zone group.

$$Average\,NRMSE\_zone_{ij} = \frac{\sum_{t=1}^{tp} NRMSE\_period_t}{tp} \tag{17}$$

where $AverageNRMSE\_zone_{ij}$ is the average NRMSE of zone j for testing day i; tp is the total number of time periods based on the examined PP; $NRMSE\_period_t$ is the NRMSE of the prediction for time period t (e.g. 10:00–11:00) calculated against ground truth data.

The NRMSE of the prediction for time period t is calculated as follows:

$$NRMSE\_period_t = \frac{RMSE\_priod_t}{\max oxx - \min occ} \tag{18}$$

where *maxOcc*, *minOcc* are the maximum and minimum occupancy value which can be observed, respectively:

$$RMSE\_period_t = \sqrt{\frac{\sum_{k=1}^{n} (\widehat{occ}_{jk} - occ_{jk})^2}{n}} \tag{19}$$

where $RMSE\_period_t$ is the RMSE (root-mean-square error) of the prediction for time period t; occ_{jk} is the actual occupancy (ground truth) of zone j at timestep k; $\widehat{occ}_{jk}$ is the predicted occupancy of zone j at timestep k; n is the total number of compared values.

Prediction is compared with the Historical Average of all the data contained into the training set as well as with the best matching relevant Open Reference model. The Historical Average contains for each occupancy zone the mathematical average of the respective occupancy values per $obsT_j$ for all training days. The *Historical Average* for a specific timestep t is calculated by the following equation:

$$Historical\_Average_t = \frac{\sum_{i=1}^{n} day_{i\_t}}{n} \tag{20}$$

where day_{i_t} is the occupancy of day_i at timestep t; n is the total number of days in the training set; $Historical\_Average_t$ is the Historical Average at timestep t.

The best matching relevant Open Reference model is selected based on the NRMSE between the Historical Average and the values of the reference model. Historical Average and Open Reference model are evaluated with respect to ground truth as well based on the same metric used for prediction evaluation (*Total Average NRMSE*).

4.2. Experimental results

4.2.1. Office

Occupancy data were collected from 5 depth-image cameras for almost 3 weeks (14 weekdays) from which 12 days were used for training and 2 days were left out for testing (random selection). The results concerning the two best Markov Chain and Semi-Markov models for various prediction parameterization and for both examined occupancy zone groups (3 zones and 1 overall zone) with respect to the Total Average NRMSE are provided in Table 8, where they are also compared against the Historical Average and the best matching Open Reference model for each zone (*Vasari_Office_Weekday*[6] for *Office_SW_02*, *Office_SW_01* and whole Office, and *BCL_Small_Office_Weekday*[7] for *Office_NE*). With bold the best result for each prediction parameterization is indicated. In the case of 3 zones, for PP1 the best model is the MC 30-0, for PP2 and PP3 the MC 20-10, and for PP4 the SM 5-0. In the case of 1 overall zone the best model for all prediction parameterizations is the MC 20-10.

As far as the prediction time frame is concerned, the results reveal that the implemented prediction mechanism (as well as the Historical Average and the selected Open Reference model) gives better results for periods close to current time (e.g. within 30 min – PP3, within 15 min – PP4) than for larger periods. Nevertheless, even in the case of 8 h after current time (PP1) the average prediction error is relatively small. Furthermore, it is obvious that the prediction mechanism in all cases examined gives far better results than the respective Open Reference model, an approach currently used by most energy simulation tools (e.g. EnergyPlus by EERE, Energy Analysis by Autodesk).

The implemented approach outperforms the Historical Average as well, giving a significant improvement in the total average NRMSE. In the case of 1 zone the difference of the best model from the Historical Average for all prediction parameterizations is higher than 8% (ranging from 8.19% to 9.31%), while in the case of 3 zones the respective difference for all parameterizations is greater than 4% and especially for PP3 and PP4 it reaches 5.75% and 7.41% correspondingly.

Furthermore, it should be mentioned that the prediction mechanism is flexible depending heavily on the current context in contrast to the Historical Average which provides a fixed value regardless of the current context. Comparing the results of the two different occupancy zone groups (3 zones vs 1 zone), it is obvious that the prediction mechanism is far better when considering the Office space as a whole. This is probably due to the fact that the 3 considered zones are not very correlated in terms of their occupancy pattern.

One graphical prediction example for a typical day (the second of the testing days) of the whole Office for PP1 based on the

[6] Autodesk 360 Energy Analysis – Vasari (http://autodeskvasari.com).
[7] https://bcl.nrel.gov/.

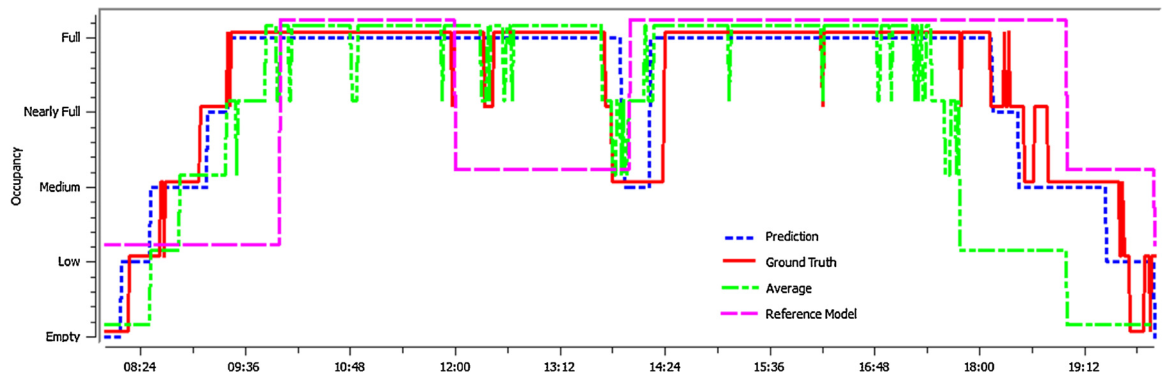

Fig. 12. Occupancy Prediction (MC 20-10) for PP1 for the second of the testing days from 8:00 to 20:00 for whole Office against Ground Truth, Historical Average and Open Reference Model.

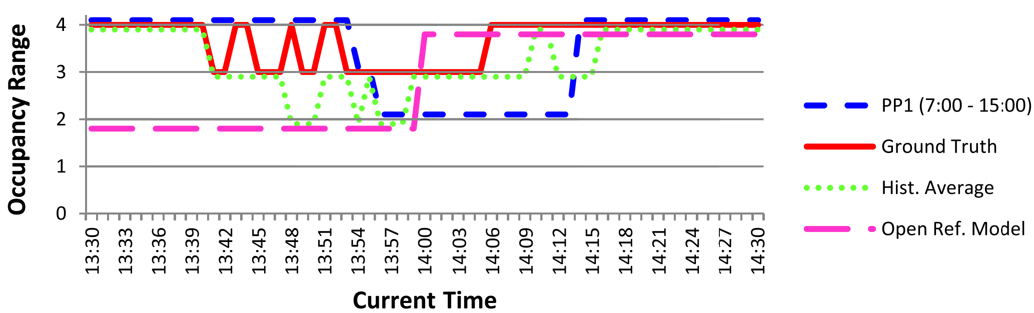

Fig. 13. Occupancy Prediction (MC 20-10) for PP1 for the first of the testing days for the whole Office (lunch time) against Ground Truth, Historical Average and Open Reference Model.

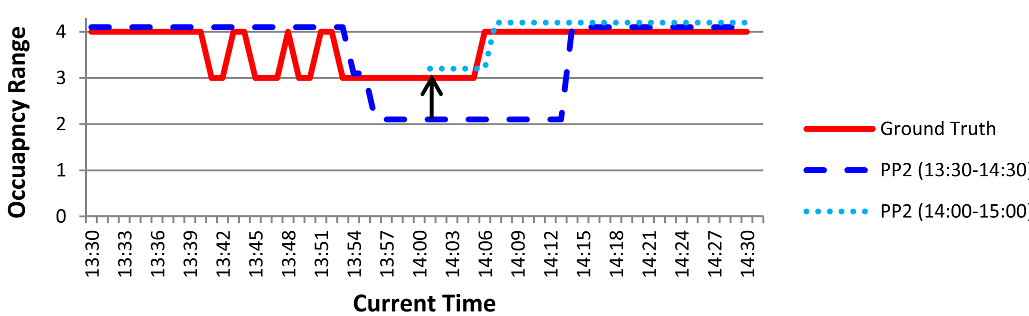

Fig. 14. Context awareness of the proposed prediction mechanism (whole Office) – Occupancy Prediction (MC 20-10) for PP2 for the first of the testing days for lunch time.

Markov Chain model 20-10 (MC 20-10) is given in Fig. 12, where the ground truth, the Historical Average and the respective Open Reference Model are provided as well. As it seems, occupants usually arrive approximately from 8:20 to 9:30, they have an intermediate lunch break at midday for about half an hour and they leave after 18:00. The prediction captures ground truth better than the Historical Average and the Open Reference Model.

To better highlight the effect of the context awareness aspect of the proposed approach, a more focused example for the whole Office targeting at lunch time (13:30–14:30), which is a period with expected fluctuation and deviation from the typical distribution, is presented below for the first of the testing days, when a non-typical situation occurred. Prediction is based on the Markov Chain model 20-10 (MC 20-10). The results for PP1, PP2, PP3 and PP4 are depicted graphically in Figs. 13–16, respectively, and they are provided in terms of the NRMSE in Table 9. The black arrows in the diagrams show the adjustment of the prediction mechanism based on current context information.

For PP1 (Fig. 13) the prediction depicted is the one produced at 7:00 for 8 h ahead, where no current context adjustment is performed (since prediction will be updated at 15:00). Essentially, this represents the case of context-unaware prediction, which is better than the Open Reference Model but worse than the Historical Average for the time period considered. In PP2 (Fig. 14) there is an adjustment in the middle, which results in the improvement of the initial prediction (PP2 (13:30–14:30)) based on current context information and eventually in the exact capturing of the ground truth.

In PP3 (Fig. 15) there are two intermediate prediction adjustments based on current context leading to the adjustment of the initial estimations. Finally, PP4 (Fig. 16) is similar to PP3 but it provides prediction for 15 min ahead with no overlapping. PP4 has the best performance although it is quite close to PP3 in this example.

In conclusion, it is obvious that the context awareness attribute of the proposed prediction mechanism is very critical, since it

Table 9
NRMSE for the examples of Figs. 13–16.

PP1	PP2	PP3	PP4	Hist. Average	Open Ref. Model
22.64%	16.71%	13.72%	12.40%	15.01%	29.34%

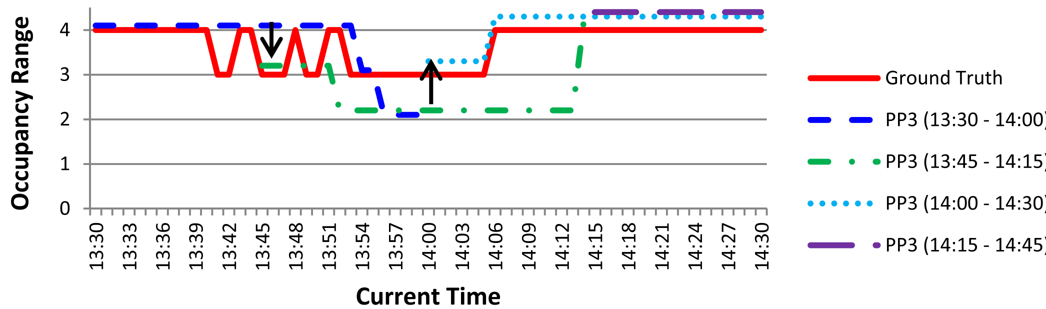

Fig. 15. Context awareness of the proposed prediction mechanism (whole Office) – Occupancy Prediction (MC 20-10) for PP3 for the first of the testing days for lunch time.

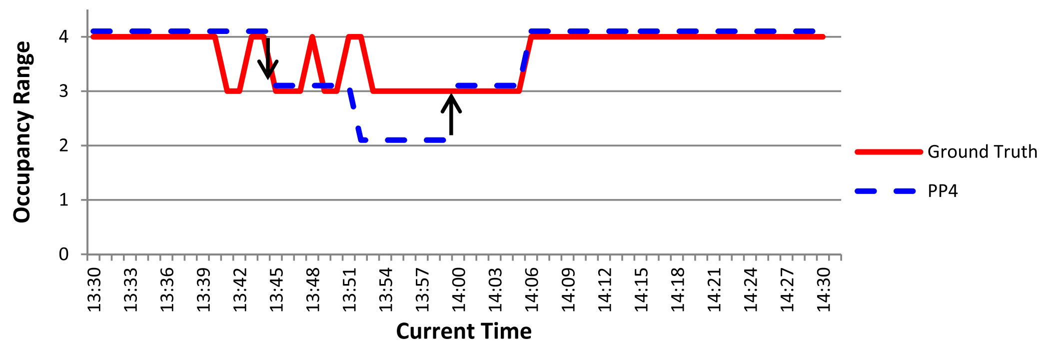

Fig. 16. Context awareness of the proposed prediction mechanism (whole Office) – Occupancy Prediction (MC 20-10) for PP4 for the first of the testing days for lunch time.

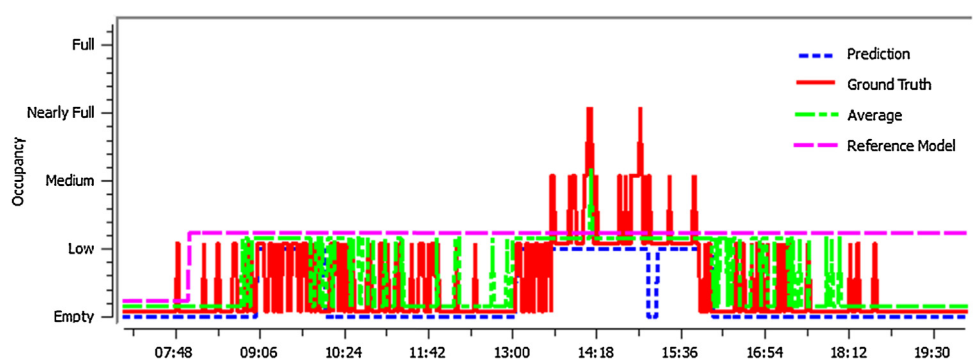

Fig. 17. Occupancy Prediction (MC 30-0) for PP1 for the first of the testing days from 8:00 to 20:00 for Kitchen_Sink against Ground Truth, Historical Average and Open Reference Model.

assists in providing more accurate estimations and enables prediction adjustment, in contrast to the Historical Average and the Open Reference model approaches which always provide fixed occupancy distributions regardless of the current context.

In order to verify that the presented results are not affected by the selection of training and testing days, another random combination has been also tested. The results are similar to the ones presented in Table 8 having only slight differences per case (average difference = 1.67%, min difference = 0.07%, max difference = 3.46%). Thus, it can be considered that the presented results are not biased.

4.2.2. Kitchen

Occupancy data were collected from 1 depth-image camera for almost 3 weeks (14 weekdays) from which 12 days were used for training and 2 days were left out for testing (random selection). The results concerning the two best Markov Chain and Semi-Markov models for various prediction parameterizations and for both examined occupancy zone groups (2 zones and 1 overall zone) with respect to the Total Average NRMSE are provided in Table 10, where they are also compared against the Historical Average and the best matching Reference model (*EERE_Food_Service*[8]). With bold the best result for each parameterization is indicated. In the case of 2 zones, the best model for PP1, PP2 and PP3 is the MC 30-0, while for PP4 the best model is MC 20-10. In the case of 1 overall zone, the best model for PP1 and PP2 is the MC 30-0, while for PP3 and PP4 the best model is the SM 5-0.

The prediction mechanism performs slightly better than the Historical Average and far better than the respective Open Reference model. It seems that the Historical Average provides adequate results in such an area with a daily repeated occupancy pattern and in some cases it could be used instead the Markov models. Nevertheless, the Historical Average has not the capability to adjust to unexpected events. Moreover, the smaller the *PredictionWindow* the smaller the error. Comparing the results of the two different occupancy zone groups (2 zones vs 1 zone), it seems that the prediction mechanism is slightly better when the Kitchen space is divided

[8] http://www.eere.energy.gov/.

Table 10
Total Average NRMSE for Kitchen.

Method	2 occupancy zones Prediction parameterization (PP)				1 occupancy zone Prediction parameterization (PP)			
	PP1 (%)	PP2 (%)	PP3 (%)	PP4 (%)	PP1 (%)	PP2 (%)	PP3 (%)	PP4 (%)
Prediction (MC 30-0)	**11.06**	**8.15**	**7.19**	6.04	**12.20**	**9.77**	8.73	7.56
Prediction (MC 20-10)	11.95	8.60	7.25	**6.03**	12.80	10.24	8.97	7.46
Prediction (SM 5-0)	15.74	9.42	7.83	6.37	16.59	10.13	**8.66**	**7.09**
Prediction (SM 55)	15.91	9.63	8.16	6.46	17.02	11.02	9.18	7.40
Historical average	11.58	8.88	8.29	7.77	12.59	10.55	10.00	9.50
Open reference model	23.68	22.55	21.98	21.48	22.54	20.95	20.37	19.88

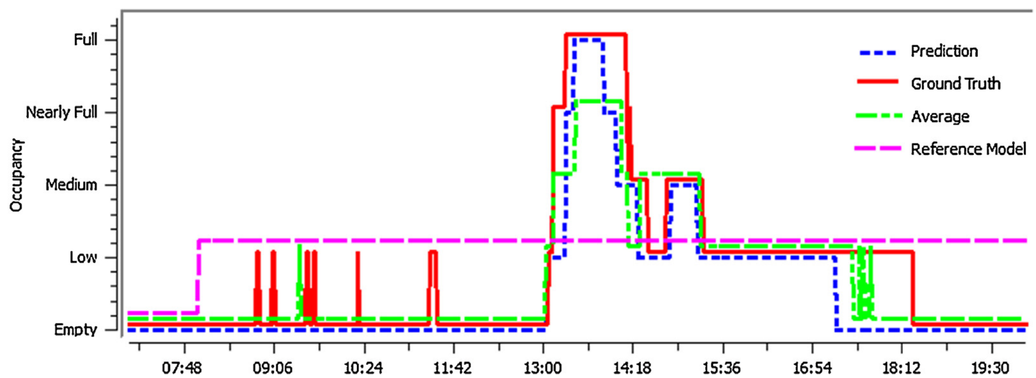

Fig. 18. Occupancy Prediction (MC 30-0) for PP1 for the first of the testing days from 8:00 to 20:00 for Kitchen_Tables against Ground Truth, Historical Average and Open Reference Model.

into 2 zones. This is probably due to the fact that there is high correlation between the 2 zones (*Kitchen_Sink*, *Kitchen_Tables*).

One graphical prediction example for a typical day (the first of the testing days) concerning the 2 Kitchen zones for PP1, based on the Markov Chain model 30-0 (MC 30-0), is given in Figs. 17 and 18, where the ground truth, the Historical Average and the respective Open Reference Model are provided as well. As it seems, *Kitchen_Sink* is usually occupied for small periods in the morning and there is a peak at lunch time, while *Kitchen_Tables* is mainly occupied during lunch time. Most occupants usually eat between 13:00 and 15:00 but there is also a group of people who eat later. The prediction and the Historical Average capture in general the ground truth in such a typical occasion and are far better than the Open Reference Model.

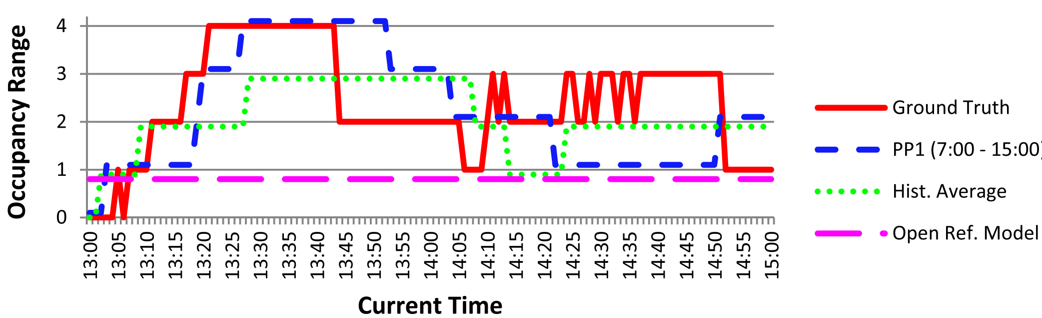

Fig. 19. Occupancy Prediction (MC 30-0) for PP1 for the second of the testing days for Kitchen_Tables (lunch time) against Ground Truth, Historical Average and Open Reference Model.

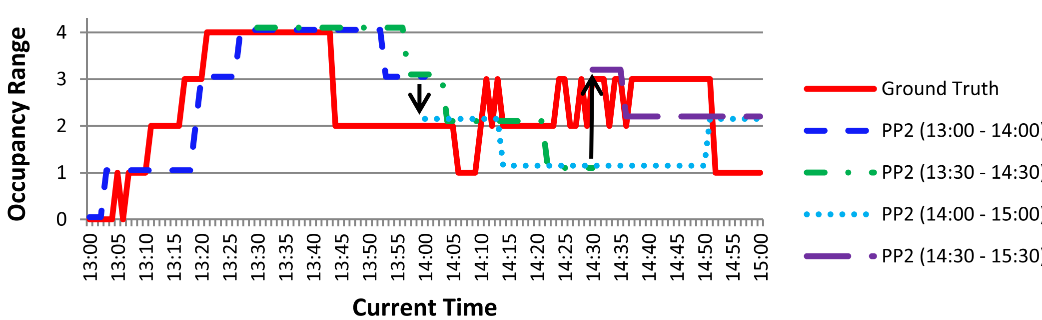

Fig. 20. Context awareness of the proposed prediction mechanism (Kitchen_Tables) – Occupancy Prediction (MC 30-0) for PP2 for the second of the testing days for lunch time.

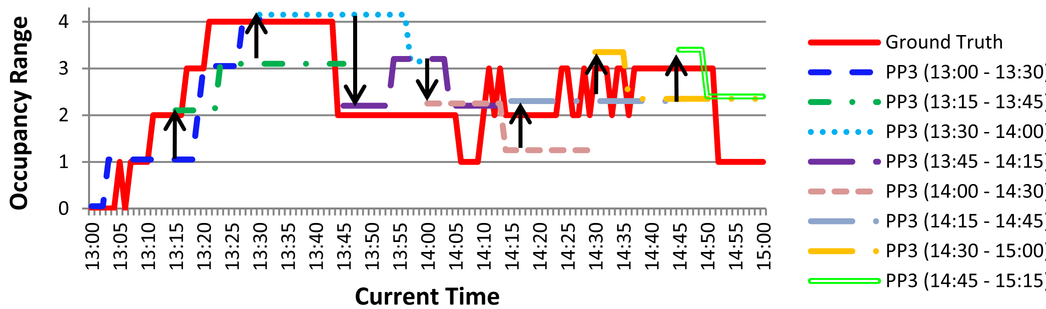

Fig. 21. Context awareness of the proposed prediction mechanism (Kitchen_Tables) – Occupancy Prediction (MC 30-0) for PP3 for the second of the testing days for lunch time.

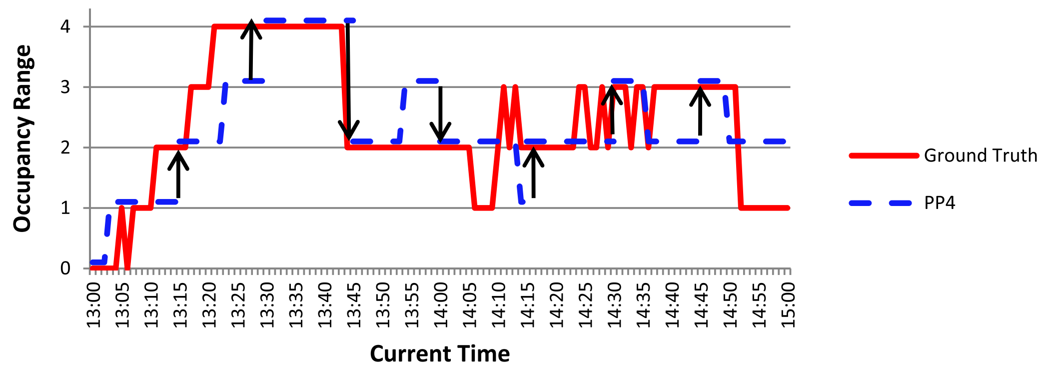

Fig. 22. Context awareness of the proposed prediction mechanism (Kitchen_Tables) – Occupancy Prediction (MC 30-0) for PP4 for the second of the testing days for lunch time.

Below a more focused example for *Kitchen_Tables* targeting at peak hours (13:00–15:00) for a not very typical day (the second of the testing days) is presented in order to better highlight the effect of the context awareness aspect of the proposed approach. Prediction is based on the Markov Chain model 30-0 (MC 30-0). The results for PP1, PP2, PP3 and PP4 are depicted graphically in Figs. 19–22, respectively, and they are provided in terms of the average NRMSE in Table 11. The black arrows in the diagrams show the adjustment of the prediction mechanism based on current context information. The Open Reference Model is the approach with the worst performance.

For PP1 (Fig. 19) the prediction depicted is not context-aware for the time period considered, since it is produced at 7:00 and will be updated at 15:00. In this case, the Historical Average performs better. In PP2 (Fig. 20) there are two intermediate adjustments, which try to improve the initial predictions (PP2 (13:30–14:30) and PP2 (14:00–15:00)) providing a better final result. In PP3 (Fig. 21) there are many intermediate prediction adjustments based on current context leading to an improved final outcome, which is better than the Historical Average. Finally, PP4 (Fig. 22) is even better than PP3 since it provides more short-term predictions and is also regularly updated (every 15 min). PP4 in this example is an indicative case which reveals the benefits of the proposed method over the Historical Average in non-typical occupancy events.

In conclusion, it is obvious that the context awareness attribute of the proposed prediction mechanism is very important, since it enables adjustments and leads to improved prediction results, in contrast to current approaches (Historical Average, Open Reference Model) which provide fixed estimations regardless of the current context. It is also worth mentioning that results are better when the current context is observed frequently (PP3, PP4) and the prediction window is short-term (PP4).

Similarly to the case of the Office, another random combination of training and testing days has been also tested verifying that the results are not biased by the specific examined selection.

Table 11
NRMSE for the examples of Figs. 19–22.

PP1	PP2	PP3	PP4	Hist. average	Open ref. model
30.66%	29.19%	23.73%	19.81%	25.91%	43.95%

Table 12
Total Average NRMSE for Rest Area.

Method	Prediction parameterization (PP)			
	PP1 (%)	PP2 (%)	PP3 (%)	PP4 (%)
Prediction (MC 30-0)	51.22	**44.64**	41.86	38.55
Prediction (MC 20-10)	51.55	44.87	42.16	38.87
Prediction (SM 5-0)	**49.71**	44.83	**41.58**	**38.49**
Prediction (SM 5-5)	54.53	45.90	42.50	39.04
Historical average	56.75	51.34	50.22	48.67
Open reference model	71.16	66.39	64.83	63.14

4.2.3. Rest area

Occupancy data were extracted based on the events collected from 1 acoustic sensor and 1 PIR sensor for almost 3 weeks (13 weekdays) from which 11 days were used for training and 2 days were left out for testing (random selection). The results concerning the two best Markov Chain and Semi-Markov models for various prediction parameterization with respect to the total Average NRMSE are provided in Table 12, where they are also compared against the Historical Average and the best matching Open Reference model (*Vasari_Assembly_Weekday*[9]). With bold the best result for each prediction parameterization is indicated.

[9] Autodesk 360 Energy Analysis – Vasari (http://autodeskvasari.com).

For PP1, PP3 and PP4 the best model is the SM 5-0, while for PP2 the best model is the MC 30-0. It is obvious that the prediction mechanism in all cases examined gives far better results than the respective Open Reference model and outperforms the Historical Average, giving a significant improvement in the total Average NRMSE (ranging from 6.7% to 10.18% for the best models). The total error is relatively high compared to the previously examined spaces (Office, Kitchen) due to the fact that the considered area presents high fluctuation and follows an irregular occupancy pattern. Another random combination of training and testing days has been also tested proving that the selection of days does not affect the results.

5. Conclusions and future work

In this paper a context-aware occupancy modelling and prediction framework has been proposed, which is suitable for real-time predictive control, implementing two different algorithmic approaches for the creation of occupancy models based on historical occupancy data and the subsequent utilization of these models along with current context information (e.g. occupancy, spatial, temporal, etc.) for short-term or mid-term prediction.

Framework evaluation, which has taken place based on real-life data, reveals that the proposed occupancy prediction method provides sufficient results, outperforming currently used approaches. Current context awareness is a very significant added value, since it provides the capability of rapidly adjusting to current conditions except just being able to predict expected events that happen on a regular basis. As it seems, model parameterization has an important impact on the final outcome, thus reliable calibration/parameterization is needed during training period in order to assure the selection of the best fitted model instance for each examined building occupancy zone group.

For future work the examination of more types of spaces, such as a single-occupant office, a space with intermittent usage (e.g. meeting room), is planned. In the case of a meeting room it is also planned to explore the incorporation of scheduling information from a room reservation system (e.g. MRBS[10]) into the prediction algorithm and study its impact on the final outcome. Furthermore, the adoption of a hybrid prediction method could be investigated concerning the utilization of a different method depending on the distance between prediction time and current time. Finally, the utilization of other predictive methods which have not been applied for building occupancy prediction (e.g. ARMA based models, SVM regression, association rule mining, etc.) could be also explored.

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[10] a free web application for booking meeting rooms.