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INTELLIGENT SERVICES FOR ENERGY-EFFICIENT DESIGN AND LIFE CYCLE SIMULATION

ISES

Deliverable D4.1+ :

Addendum

to Deliverable D4.1 "Technical specification of the overall framework and the principal energy profile and consumption patterns" –

Stochastic energy profiles and consumption patterns

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Project of the SEVENTH FRAMEWORK PROGRAMME OF THE EUROPEAN COMMUNITY		
Dissemination Level		
PU	Public	**X**
PP	Restricted to other programme participants (including the Commission Services)	
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TABLE OF CONTENTS

Executive Summary

Deliverable **D4.1** (Gudnasson et al. 2012) provided the conceptual bases, specific requirements and specification of the overall data and services framework and the definition of the stochastic templates. Early planning of work tasks required a shift of planned work for the implementation and software development for the stochastic approaches elaborated in task 2.1 to WP4. This required a amended version of deliverable D4.1 accepted by the project officer.

This follow-up document named **D4.1+** and prepared as an addendum to D4.1 includes an overview of the methodology, principles and application examples for the stochastic approaches that are being implemented. The types of data that are being addressed include stochastic sampling for **material properties** and **occupancy**, and semi-stochastic **weather/climate** data.

The use of the developed stochastic software components is documented in D4.2.

The work on this task is performed by the following **partners**:

- **NMI** – stochastic material properties and constructions and related software development, integration in the Simulation Resource Framework, reporting, deliverable lead
- **NOA** – semi-stochastic weather/climate data and climate tool, integration in the Simulation Resource Framework, reporting
- **TUD-CIB** – stochastic occupancy sampling and related software development, reporting

1. Introduction

Accounting for the variability of input data over time during simulations can provide more realistic results to accurately predict the actual energy performance of a building. The three major sources of uncertainty in building energy simulations are (Zahedi Khameneh et al. 2012):

- Material properties
- Weather/climate
- Occupancy

The variations of input data is usually based on fluctuations observed in historical data for a selected period using standard time-series techniques. Distributions of potential outcomes are derived from a large number of simulations (stochastic projections), which reflect the random variation in the input.

For **material properties**, an efficient and robust stochastic simulation is based on the Monte Carlo technique, which is improved by applying a reduced variance sampling approach (i.e. Latin Hypercube Sampling).

For **weather/climate data**, the approach is to compare annual weather data against climate (average) data over a long period of time (Test Reference Year), for a given location, in order to generate different weather patterns (e.g. coldest, warmest, windiest) annual weather data.

For **occupancy**, different occupancy samples are used to generate stochastic occupancy profiles for independent zones or potentially for neighbouring zones of a building, and different time segments.

The following sections present an overview of the methods used to generate the variable input data for material properties, weather/climate data and occupancy.

2. Material Properties

Manufactured building products can exhibit variability in their technical properties that can be influenced by different factors, e.g. normal variation in the manufacturing processes, precision and quality control, calibration of production machinery, inhomogeneous nature of production materials and other factors influencing the manufacturing process (Zahedi et al. 2012).

Figure 1. Multi layered building material

Building elements serve as zone boundaries between zones with different thermal properties, e.g. external walls in the building envelop or building parts surrounding a server room with severe internal heat gains and high cooling needs. A U-value is a measure of how well a building element such as a wall, floor or roof transfers heat through its cross section. Building element thermal performance or U-value is a function of the thermal properties of the individual material layers assembling the element.

In stochastic energy simulation, variability in material thermal properties like thermal conductivity (λ), material density (ρ), specific heat capacity (c) and material thickness (t) may be considered stochastic variables in the simulation model. Random sampling techniques are used to generate a representative sample of the total population from a given probability distribution. The normal distribution or log-normal with mean (μ) and standard deviation (σ) are considered a sufficient estimate for material thermal property variability.

The Latin Hyper Cube method is a probabilistic technique widely used to evaluate multivariate functions when the function is dependent on an estimate of the function variables rather than their exact values. The Latin Hyper Cube method can be applied effectively to calculate or approximate the U-value of a building element, where the thermal properties of individual material layers are considered to be uncertain and need to be estimated by probabilistic methods based on probability distribution of thermal properties.

Latin Hyper Cube Sampling

The Latin Hypercube Sampling (LHS) method developed by McKay in 1979 and further elaborated by Iman in 1981 (http://en.wikipedia.org/wiki/Latin_hypercube_sampling) is a special case of the stratified Monte Carlo sampling method.

It has been shown to reduce necessary sample sizes, over simple random sampling method while ensuring full coverage over the range of the random variable and thereby eliminating problems associated with clustering and gaps (bias) in the sample distribution.

To generate a sample size N of a function with K variables, $X=[x_1, x_2, ..., x_K]$ with probability density function $D_1, D_2, ..., D_k$, is done as follows. The probability distribution D of each variable is divided into N non overlapping intervals of equal probability, thus stratifying the distribution into N number of intervals. The next step is to take N random samples for each variable X form as the inverse Cumulative Probability Function of D_i (i=1,k) $F^1(X)$, one in each interval. The sample for each variable X_i (i=1,k) is then a vector of N rows.

The Latin Hypercube, a square grid, is then assembled satisfying the Latin square principle if and only if, there is only one sample in each cell of the grid (row, column) as follows. The N values in the vector rows of variable x_1 are paired randomly with values of vector rows of x_2 (e.g. by applying random permutations to the index of the vector). The pairs are then paired in a similar fashion with values of vector of x_3 and so on, until a matrix of N samples for the x and k variables is formed (Matala 2008).

The function $Y(X) = F(x_1, x_2, ..., x_K)$ can then be evaluated for each sample n_i (i=1,N) of k values to estimate the probability distribution of Y.

The LHS may be summarized as follows:

1. divide the cumulative distribution of each variable into N intervals with equal probability
2. from each interval randomly select one value, for any interval i, $P_i = (1/N)rand(u) +(i-1)/N$ where rand(u) is a uniformly distributed random number in the range 0-1
3. calculate the values based on the probability value using the inverse of the distribution F^1 such that $x = F^1(P_i)$
4. the N values that are obtained for each variable x are then randomly paired with the values of other variables thus forming the Latin Hyper Cube
5. Evaluate the function $Y = F(x_1, x_2, ..., x_K)$ for each row n_i (i=1,N) in the Latin Hyper Cube,

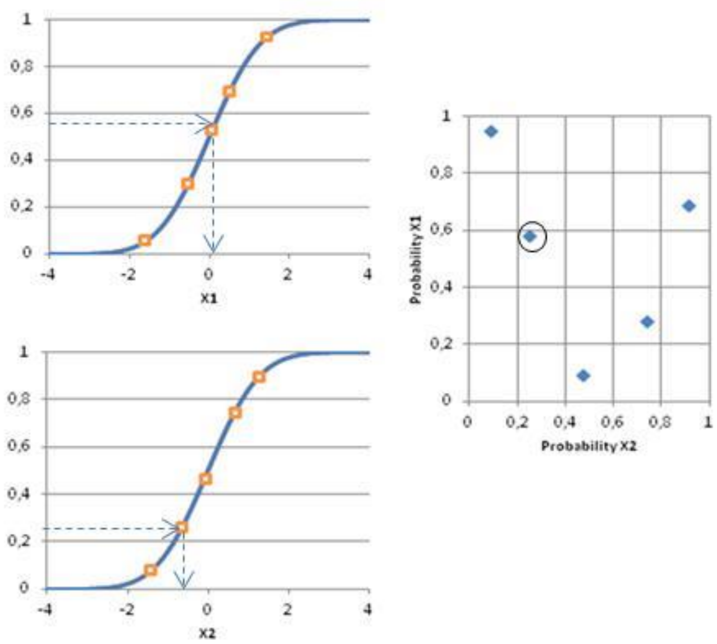

Figure 1. LHS example of two normally distributed variables X1 and X2 with random pairing of X1 and X2 forming a Latin Hyper Cube

Thermal conductivity of materials and U-values of building elements

The design values for thermal properties are commonly required for heat transfer calculations in buildings. Design values can be derived from declared values that are normally based on laboratory measurements provided by the manufacturer. Thermal properties of building materials are covered by a harmonised European standard (EN) or a European Technical Approval (ETA), product declarations and should conform to the requirements of the EN or ETA. Otherwise, thermal conductivity of an insulation material may be declared by a manufacturer according to e.g. EN ISO 13162.

The declared thermal conductivity λ_D shall be given as the calculated conductivity $\lambda_{90/90}$ rounded up to the nearest 0.001 W/mK; where

$$\lambda_{90/90} = \lambda_{mean} + k \cdot s_\lambda$$

and

$\lambda_{90/90}$ a limit value representing at least 90% of the production, determined with a confidence limit of 90%

λ_{mean} average measured thermal conductivity

k factor based on significance level and number of specimens (100 specimens, k=1.47, 500 specimens k=1.36)

s_λ standard deviation of measured conductivity

The above recognises the uncertainty in declared values for thermal properties of materials. For each material layer the variables (e.g. material thickness, thermal conductivity and thermal resistance) have a statistical variation and accordingly an uncertainty in the overall heat transfer co-efficient (U-value) of layered building elements.

The U-value of a building element is defined as the reciprocal of all the thermal resistances of the materials found in the building element, where the thermal resistance of a material is a function of the thermal conductivity and martial thickness expressed by $R_i=d_i/\lambda_i$, whered is the material thickness and λ is the thermal conductivity of the material.

The U-value of a building element is calculated as;

$$U = 1/R_T = 1/ \Sigma (d_i/\lambda_{i,})$$

where $R_T = \Sigma (d_i/\lambda_{i,})$ is the total sum of thermal resistances for all material layers in the building elements, including surface resistances.

Latin Hyper Cube method applied to U value calculation of building elements

To illustrate the use of the Latin Hyper Cube sampling method for evaluating the probability distribution of a building element U-value, a wall elements is used consisting of four uniform material layer as shown in Table 1. Surface resistances Rsi and Rse are not shown as simulation programs use different methods in accounting for them - some add them automatically to material assemblies while others do not.

In this example, thermal conductivity values are considered as stochastic variables, each having a normal (Gaussian) distribution with mean μ and a standard deviation σ.

Table 1. Thermal conductivity of materials in a wall

	Thermal conductivity (W/mK)	
Material Layer	(μ)	(σ)
Rendering (interior)	1.24	0.12
Insulation (ESP)	0.033	0.002
Concrete	1.7	0.2
Rendering (exterior)	1.4	0.12

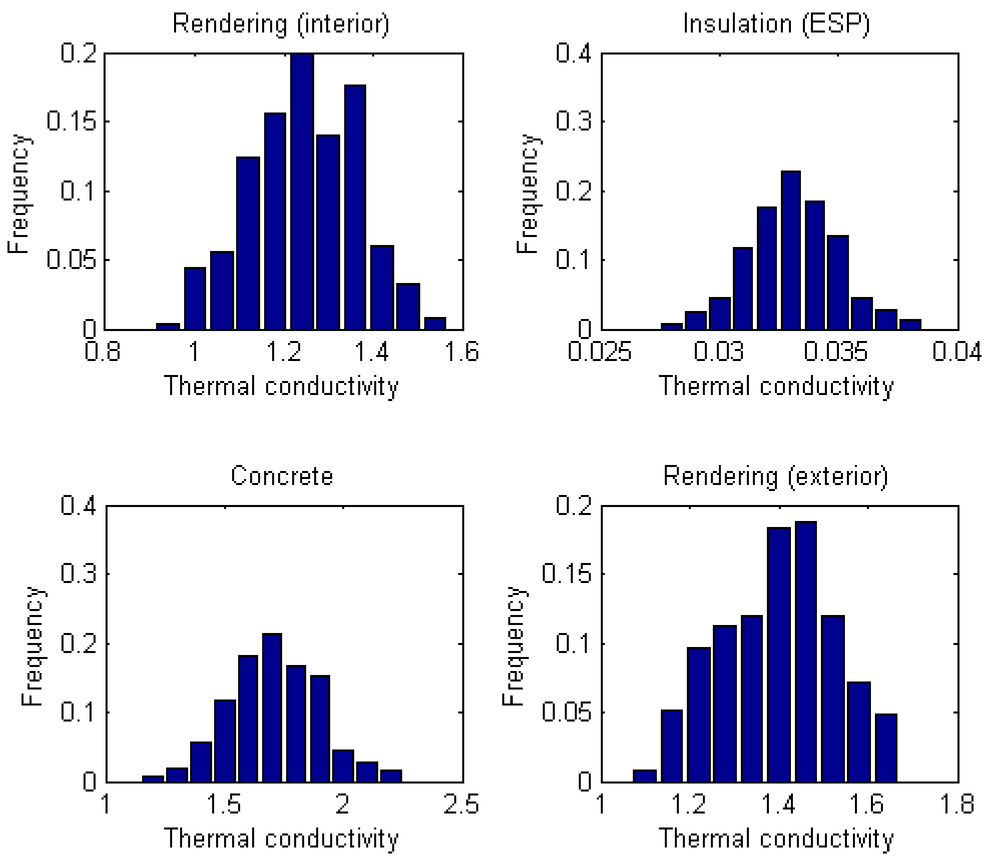

Figure 2. Distributions of samples drawn for individual material layers

Each of the material thermal conductivity normal distributions were sampled (as shown in figure 2) by drawing 50 samples from a uniform distribution in the range of 0-1 that were subsequently transformed to thermal conductivity values based on the respective normal quantile function. The samples where then randomly permuted in order to calculate the U-value for each sample. The resulting U-value distribution is shown in figure 3. As illustrated in the figures, the distributions are approximately normal. A better normal distribution would be achieved with increased sample size.

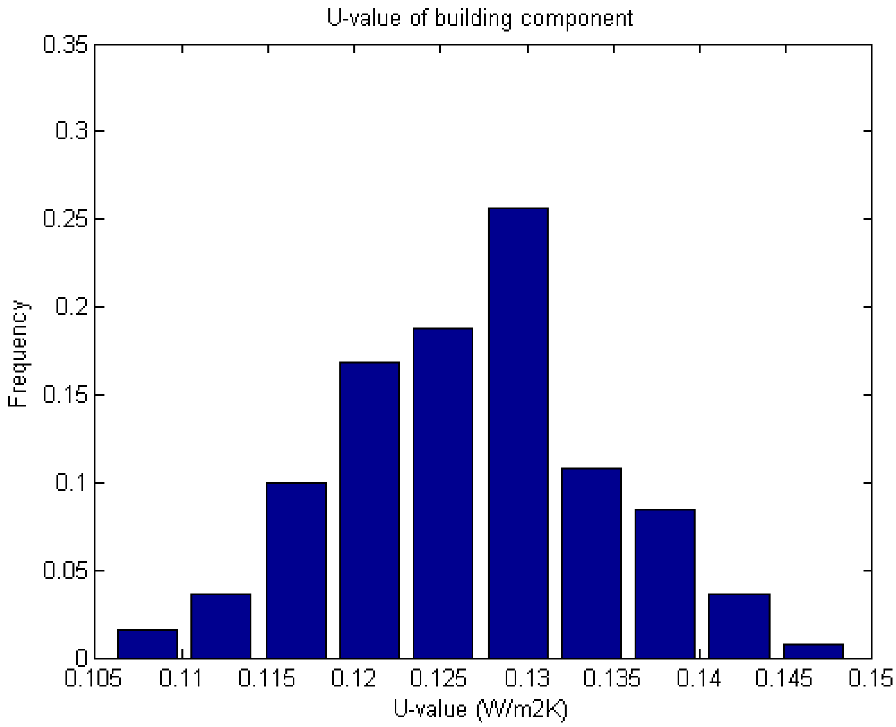

Figure 3. Distribution of the building element U value as calculated by the LHS method

The method described has been implemented as software integrated in the template processing engine, enabling automatic generation of the stochastic data sets for 1) any material property and 2) stochastic U value estimation based on EN ISO 6946 and Latin Hyper Cube Sampling for building elements were special template tags as described in (Gudnason G., et al., 2013) embedded in the templates control the sampling procedure.

3. Weather/Climate Data

The need for appropriate climate data for long term prediction of the annual energy performance of buildings (e.g. thermal comfort conditions, heating and cooling loads) with relatively low computational time has led to the development of the Test Reference Years (**TRY**). They are commonly composed of hourly values for a one year period (12 typical meteorological months) rather than extreme conditions of measured weather data. TRYs provide hourly data of outdoor temperature, humidity, wind, solar radiation and possibly other meteorological parameters for a period of one year (8760 hourly records), representing conditions considered to be typical over a long time-period (e.g. 10-, 20- or 30-years). TRY data have natural diurnal and seasonal variations and represent a year of typical climate conditions for a location, preserving the main local weather characteristics, e.g. typical cold or hot conditions, but consistent with the local long-term averages. However, TRYs are not suitable for calculating peak heating and cooling loads for sizing HVAC systems. In addition, simulation results may also deviate from actual performance, thus resulting to misleading assessments of energy savings or improper selection of design options, depending on possible deviations from actual weather conditions.

Generating synthetic data representative of future conditions can be facilitated by an assessment of previous long records of measured data that reveal valuable insight on possible extreme conditions. This kind of analysis can be facilitated by a "**Weather & Climatic Data Tool**" that may be used as a standalone application (.net) to process long records of weather data and how they compare against a typical TRY. The results could illustrate the most likely high or low values of different weather data with respect to a specific parameter (e.g. temperature, wind, pressure, solar radiation) and reasonable ranges. Using this insight, one can then **generate weather patterns** for future extreme conditions (e.g. hot and/or cold conditions).

Summer and winter design conditions are usually available for different locations, which are often adapted by building designers and engineers to meet local design practices and conditions. It is also common practice to introduce arbitrary safety factors to ensure that the size of the HVAC equipment would meet extreme conditions. This often results to oversized equipment and thus significantly higher energy consumption under part load operating conditions. Adequate and economical equipment sizing can be achieved by using the appropriate weather data in building thermal simulations.

Quantifying and assessing the significance of extreme conditions can be facilitated by analyzing long records of weather data in order to select a weather file that contains the most adverse winter conditions, instead of the TRY. For example, considering that the design outdoor temperature for Athens is -2^{o}C for winter, one could screen the entire time series of available weather data for the coldest, compared to a TRY as shown in the following figure. A graphical representation reveals the percentage of occurrences for the specific conditions, during the year. As shown, the lowest extremes on record according to the available time series appear in 2004 with 0.4795% hourly occurrences during the year or 42 hourly records with T<-2^{o}C. Accordingly, instead of using the TRY, one could select to perform the simulations for heating loads using 2004 winter weather data. The statistical occurrences of these extreme events could also be evaluated on a seasonal basis (heating or cooling periods) or on a monthly basis.

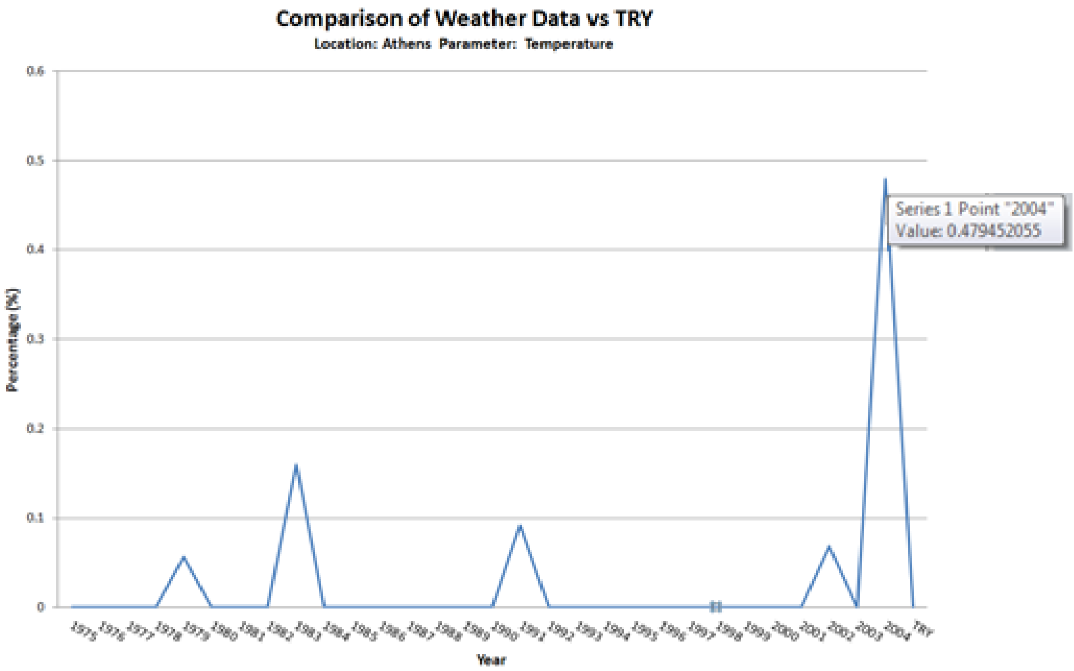

Figure 4. Percentage of occurrences for extreme cold with T<-2^{o}C weather conditions compared to typical conditions (TRY) for Athens, Greece.

Additional criteria should also be taken into account by selecting more weather parameters at the same time, in order to account for their combined impact. For example, specifying adverse summer conditions that would result to higher (sensible and latent) cooling loads one should look at both high temperature and humidity. In this case, one could refer to the resulting statistics that correspond to the statistical occurrences of combined criteria (Temperature>38^{o}C .AND. Relative Humidity>60%).

The analysis of the historic weather patterns can reveal the occurrences of possible extreme conditions. Accordingly, the outcome of this effort would be to perform the simulations by

a) **selecting** a **specific year** that best reflects the anticipated (desirable) extremes;

b) **generating** suitable **weather patterns** under different criteria. This may be achieved by modifying the TRY file using data from selected (extreme) years for heating or - and cooling period, or considering all time series of available annual data sets. Conditions for selected parameters may refer to criteria for maximum, minimum or design conditions (e.g. 99.6% for the heating period or 0.4% for the cooling period).

The calculation of peak heating and cooling loads, mandate the use of minimum and maximum outdoor air temperatures that account for sensible loads and possibly coincident outdoor humidity in order to account for latent loads. Design conditions of 99.6% are also common practice for peak heating load calculations thus ensuring that the heating system is sufficiently sized to handle the coldest expected temperatures (Figure 5). This means that the actual hourly temperatures are greater (warmer) than the design temperature 99.6% of all annual hours. These values represent, for example, the outdoor temperatures corresponding to 99.6% annual cumulative frequency of occurrence (cold conditions). Different percentiles, for example 99.0%, are also common practice.

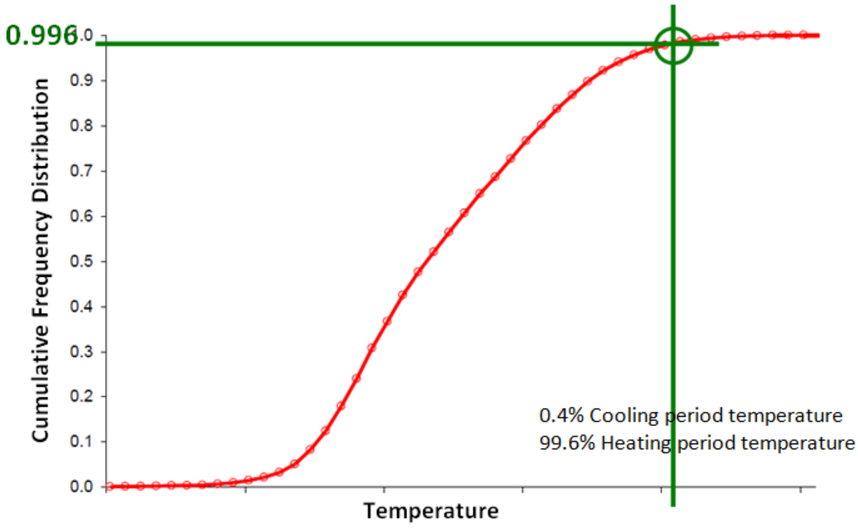

Figure 5. Cumulative frequency distribution function for calculating the 99.6% heating and 0.4% cooling period temperature.

For peak cooling load calculations, the 0.4% design conditions for temperature and humidity ensure that the cooling system is sufficiently sized to handle the warmest expected conditions. In this case, the temperature and humidity conditions are based on annual percentiles of 0.4, although others are also common, for example, 1.0%, 2.0%, 5.0% or even 10.0%.

Accordingly,

x% design condition = 'conditions exceeded x% of time'

where the annual design conditions, for example, 99.6% heating period temperature, 0.4% cooling period temperature are taken

The generated annual file (8760 hourly values) should be composed by setting different criteria for specific periods during the year or throughout the year, for modifying the TRY. For example, the **coldest weather pattern** can be achieved by comparing and selecting for each hour of the day during winter (October-April) the corresponding minimum hourly data that may occur during the entire time series or selected years. The **warmest weather pattern** may be generated by selecting for each hour of the day during summer (May-September) the corresponding maximum temperature. Similarly, this may be also applied for selecting the **windiest & coldest** conditions during winter that may be combined with the coldest weather conditions in order to derive a weather pattern of adverse winter conditions.

Any **other possible combinations** of extreme weather parameters or design conditions for the heating and/or cooling period should be possible. In all other cases, the corresponding typical (TRY) data are available. For completeness, any additional weather parameters that may be necessary by the simulation tools (e.g. wet bulb temperature, direct normal solar radiation) should be calculated based on the corresponding data that have been derived with the various criteria, to obtain as output a complete annual weather file for performing the simulations.

4. Occupancy

Stochastic occupancy patterns of a building zone can be created based on measured occupancy data (e.g. available from ISES partners like Granlund or TUD-IBK). These patterns represent the occupancy depending on the different building functionalities (e.g. office, residential) and can be associated with several zones or building spaces (Figure 6). An occupancy pattern represents a profile which describes the occupant presence zones or building spaces expressed as a percentage over time.

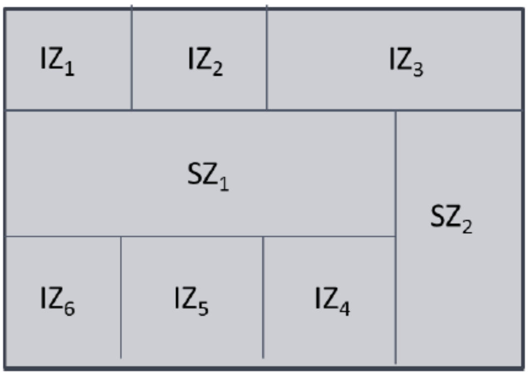

Figure 6. Buildings are divided in different zones (rooms).
There are individual zones (IZ; occupancy profiles are independent of each other)
and shared zones (SZ; occupancy profiles depend on adjacent individual zones).

The occupancy sample generator produces stochastic occupancy profiles for independent zones or potentially for a sharing zone to consider the dependency between several zones of a building. Along the time axis, the occupancy profile (pattern) is characterized by several segments. Each segment is described by a start- and an end-value (Figure 7). The activity trend is assumed constant within the segment. In order to model the stochastic character of occupancy, the values at a start and an end point of the segment are described by mean and standard deviation values. In this manner, based on defined characteristic occupancy profiles for particular zones and time intervals (working days or weekends) several stochastic patterns can be created.

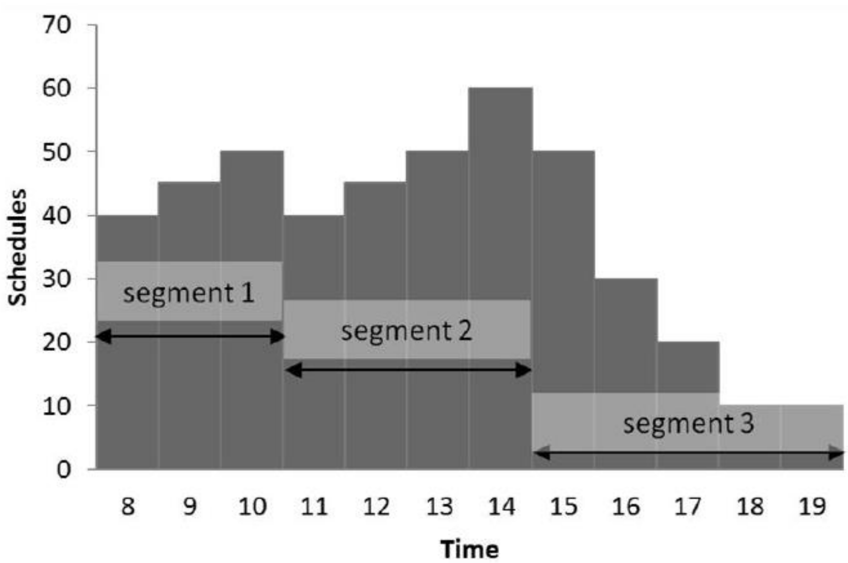

Figure 7. Example segments of an occupancy pattern.

Sample Generator

Stochastic data sets are dynamically generated by the sample generator. The sample generator and stochastic processor are embedded in the template processor. The process is facilitated by a **sample generator** that provides number of samples schedules for hourly occupancy values over a whole year. It is written in Java and implements an interface with a function "createSamples" that builds the stochastic sampled schedules.

The input parameters to "createSamples" are the:

- number of samples to be generated
- index of the relevant zone
- array of the various patterns from which the particular pattern is selected
- mapping of patterns to zones.

The output is a two dimensional array, with number of samples as the first dimension and hourly values as the second.

The different input patterns are kept in an array of patterns. The array of patterns are then stored in a library as well as the mapping of patterns to zones.

Each pattern contains an array of segments. Patterns can contain a different number of segments. In particular, the segments itself are characterized by the:

- start time
- mean value of occupancy at start time
- standard deviation of occupancy at start time
- end time
- mean value of occupancy at end time
- standard deviation of occupancy at end time

Finally, the stochastic generated samples can be integrated in the simulation configuration files by the simulation configurator together with all necessary data to accomplish a complete simulation.

5. Conclusion

This document complements the work reported in Deliverable D4.1, expanding and providing a more detailed view of the methodologies and the necessary specifications for handling the stochastic sampling for material properties, occupancy and semi-stochastic weather/climate data. The sampling software will be integrated in the Simulation Resource Framework (SRF) on the virtual energy lab platform. The stochastic sampling can thus be handled using the stochastic energy enhancement templates that are elaborated in Deliverable D4.4.

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