Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria Meccanica e Gestionale

Development of a methodology for the optimal sensor placement to optimize air temperature monitoring in large spaces.

Ph.D. Dissertation of:
Federico Seri

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To my family
Om

Acknowledgments

"Turn problems into opportunities" is one of my favourite sentences and I think that it really embodies the meaning of doing a PhD career. First of all, I would like to thank Professor Gian Marco Revel, which gave me the chance to be part of the research group of measurement, guiding me to grow as a professional and as a person during these years. I would like to thank Professor Enrico Primo Tomasini, who is the founder of this research group and Professor Nicola Paone for the availability on technical and educational support. Another thank goes to Professor Marcus Keane founder of the IRUSE research group and to all the members. He gave me the possibility spent a six months research experience with the IRUSE group in Galway, thanks to all the IRUSE researchers for the technical support and for the great craic. I express gratitude to my colleagues that helped and encouraged me during these years. Finally thank to my family and friends for sharing with me the pains and the gains of this experience. Never give up and enjoy your life.

Ancona, Gennaio 2016

Federico Seri

Abstract

The present PhD thesis summarizes the development and validation of a tool called Sensor Optimization Unit (SOU), meant to be used by HVAC engineers, for the optimization of temperature sensors placement in large spaces, where the HVAC system provides indoor thermal comfort conditions, which involves mostly air temperature control, without taking into account the indoor air temperature distribution inside the space on the monitoring task. The SOU allows approaches based on simulation model, field measurement or calibrated simulation model to characterize the indoor horizontal air temperature distribution. A modular optimization approach based on a novel measurement performance index is proposed, which evaluates the sensor network design, determining the optimal sensors location that provides the maximum measurement accuracy, using the minimum number of sensors. The optimization process evaluates, also, the impact of the measurement deviation on thermal comfort and energy consumption due to HVAC operation. The entire methodology was applied and validated on three different case studies. The incorrect placement of an existing thermostat, inside an indoor swimming pool, showed that the measurement uncertainty was higher than the sensor uncertainty (value from sensor datasheet) for the 42% of the period considered. The optimized sensor network design decreased that period to 1.5% of the overall time. The entire optimization procedure was also applied to a fitness room. The optimal monitoring solution retrieved by application of the measurement performance index was compliance with the one calculated as measurement uncertainty impact on thermal comfort and energy consumption. The measurement performance index was applied to an open space office equipped with a widespread set of temperature sensors controlled by a BMS. The selection of two of the six sensors available, still assuring a measurement accuracy inside the uncertainty of the sensor.

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Chapter 1

Introduction

1.1 Background and motivation

Monitoring spatial phenomena as indoor air temperature is a challenging task, especially when applied to large indoor spaces. Large spaces include indoor sport spaces, open space office, entertainment buildings, cruise ship, aeroplane, where the air temperature is not homogeneously distributed, so the monitored values can be different from point to point at a given instant. In particular, phenomena as air stratification and stagnation may be present, causing significant horizontal and vertical temperature gradients [1]. This phenomena are generally due to large floor area, high height, high percentage of glazing surfaces, incoming direct solar radiation, errors on ventilation system design and heating/cooling sources randomly distributed in the space. The indoor thermal condition are normally monitored using traditional methods as single point temperature sensors, usually located in the return duct of the ventilation system or in a single point of the space, without taking into account air temperature gradients that could occur in the occupied space. Additionally, common practise is to design a monitoring system using criteria based on experience. So, conventional air temperature monitoring techniques could reach a level of measurement uncertainty that prevent accurate thermal comfort evaluation [2, 3] and effective climate control strategies operated by the HVAC (Heating, Ventilating and Air Conditioning) system [4, 5, 6]. Considering that measuring the air temperature inside critical environments, such as large spaces, using a limited number of sensors, is a challenging task to achieve; so the decision making process leading to selection of sensors number and placement is challenging too. Considering what said above, a dedicated methodology focused on sensor network design optimization, in terms of sensors number and locations, taking into account the impact on thermal comfort and HVAC operation, deserves to be investigated.

1.2 Current approach

Different methodologies have been developed to achieve the indoor air temperature monitoring optimization. For instance, [7] developed and applied a methodology coupling CFD (computational fluid dynamics) and GA (Genetic algorithm) to define the optimal placement of temperature sensors in a single zone. [8] proposes a strategy for using wireless sensor network to monitor the temperature distribution in a large-scale indoor space, improving the quality of the measurements, identifying the temperature distribution pattern of the large-scale space, and optimizing the allocation of multiple supply air terminals. [9] uses a CFD calibrated model to generate a reduced order model to reproduce the indoor air dynamics allowing the rooftop units (RTs) assessment.[10] proposes a CFD-BES co-simulation strategy through indoor temperature sensor placement optimization linked with HVAC energy consumption and thermal comfort. The paper [11] proposes a CFD based supervisory demand-based temperature control applied to large-scale room to improve HVAC control and energy performances. In [12], a methodology based on CFD model was developed for sensor placement optimization on a Greenhouse environment. [13] proposes a CFD model approach for optimal wireless sensor nodes installation in large-scale room. [14] presented a "quasi-3D" modelling approach for thermo-hydraulic simulation of airflows and used it to investigate heaters and sensors positioning issues in a room. [15] proposes an ESP-r model approach to investigate the influence of temperature sensor placement on the heating energy consumption and thermal comfort. While, [16] developed a dedicated zonal model to study the influence of the sensor positioning in building thermal control. [17] proposed a zonal model to investigate the applicability of a new approach designed for prediction of energy consumption of a residential building, equipped with and underfloor air distribution system (UFAD). On the contrary, [18] proposed a data-driven approach to model the thermal dynamic of a large space through a combination of data clustering and system identification techniques. This approach attempts to reproduce the dynamics of the environment in a very accurate way and requires a fine-grained instrumentation measuring for a long period. The data mining procedure is also applied in [19] to analyse off-line dataset and investigate the distributions of indoor air temperature, humidity and lighting in an indoor environment. [20] presented a method that provides analysis of measured data to reduce the number of sensor nodes deployed while preserving the quality of the information. Tab. 1.1 summarizes key features as measurement approach for thermal characterization of the space, methodology for the dataset generation, optimization strategy and objective for the proposed studies.

Table 1.1: Literature review key features

Ref.	Space	Measurement	Dataset	Optimization	Objective
[7]	Small	Spatial air temperature distribution	CFD	Balance between measurement accuracy and infrastructure costs	Optimal air temperature monitoring based on measured data and CFD model.
[8]	Large	Horizontal air temperature distribution	CFD	Optimizes the supply air flow rate allocation according to temperature distribution pattern	Optimal supply air flow rate allocation.
[9]	Large	RTUs supply and return air temperatures, external temperature	CFD	Sensor retrofit analysis	Sensor retrofit analysis linked with thermal comfort and RTUs energy usage.
[10]	Small	No measurement	CFD	Sensor retrofit analysis	Sensor retrofit analysis linked with thermal comfort and HVAC energy usage.
[11]	Large	Sensor network at breathing level	CFD	Optimal HVAC control strategies	Thermal comfort and HVAC energy usage.
[12]	Large	Horizontal air temperature distribution	CFD	Optimal sensor placement	Optimal temperature monitoring and model calibration.
[13]	Large	Horizontal air temperature distribution	CFD	Optimal sensor placement	Optimal temperature monitoring and model calibration and HVAC control.
[14]	Small	3D air temperature distribution from MINIBAT test cell experiment and simulation	Zonal model	Sensor position retrofit linked with heating control system	Optimal sensor positioning linked with optimal room heating control and model calibration.
[15]	Small	Meteo station and indoor air temperature	ESP-r	Sensor position retrofit linked with heating control system	Impact of sensor placement on the heating thermal consumption and thermal comfort.
[16]	Small	Air temperature vertical gradient	Zonal model	Vertical temperature monitoring	Impact of sensor placement on vertical temperature gradient.
[17]	Small	Air temperature vertical stratification	Zonal model	Vertical temperature monitoring	Prediction building energy demand.
[18]	Large	Spatial thermal distribution, rate airflow blown from the HVAC, occupancy detection	Dynamic data-driven model	Model development, validation and sensor clustering	Optimization of the HVAC control based on sensor clustering and dynamic data-driven simulation model.

Ref.	Space	Measurement	Dataset	Optimization	Impact
[19]	Large	Horizontal air temperature distribution, relative humidity, light level	Data driven	Data mining to understand distribution of environmental parameters	Development of methodology to predict temperature map of the space.
[20]	Small	Spatial air temperature distribution, humidity and light level	Data driven	Sensors reduction	Development of a methodology based on sensor clustering to reduce the number of sensor nodes.

According to the studies reported in Tab. 1.1 and the features of large spaces, the following outcomes are pinpointed:

- the horizontal air temperature distribution is one of the main physical property to be identified for climate characterization of a controlled large space;
- HVAC layout, user profiling, outdoor conditions (e.g. solar radiation magnitude and direction, neighbouring buildings, shadowing elements and seasonal climate variation) are the key factors to characterize, in both dynamic and static manner, allowing simulation or data driven approach to capture the thermal behaviour of a controlled space;
- indoor spaces are typically controlled by HVAC systems, by means of a feedback loop, through a single point temperature sensor placed along the perimeter of the space or on the return duct;
- a widespread of temperature sensors is usually deployed for thermal characterization of large spaces, considering layout barriers for sensor placement, particularly in this type of environment;
- a review on the founded algorithms, solving the sensors placement optimization issue, related to optimal temperature monitoring, highlighted that a unique recognised criteria is missing.

Considering the Tab. 1.1 and the outcomes, reported above, a CFD model [7, 8, 9, 10, 11, 12, 13] “provides far more accuracy, but has at least two drawbacks. The first and obvious one is complexity. The second is that it is not immediate to separate the (partial) differential equations that hold within a volume from the boundary conditions. The creation of modular models is thus a complex task, in some cases unavoidably leading to quite cumbersome software implementation. There exist CFD tools applied to buildings, e.g., Fluent [21], but they are mostly used for steady-state computations, and hardly ever considered in system-level stud” as outlined in [14]. In fact, a CFD model solves Navier-Stokes equations and calculates physical parameters usually not measurable with the same level of detail. However, the requirements in terms of problem definition, computational effort and time consuming processing, make it not suitable for the implementation and design within a general building simulation program and control technology field. Moreover, the changes of interior layout and continuous fluxes of occupants during a day, typical of large spaces, can have a strong impact on the reliability of the CFD model. To overcome these issues, the studies [14, 15, 16, 17] developed a methodology based on both zonal model and measurements to calibrate and validate the simulation model, making it able to optimize the climate control of the space through optimal sensor deployment. The proposed zonal models need less computational requirements compared with the CFD model, providing optimal results in terms of prediction of the air temperature distribution. On the other hand, they were developed to be applied on specific domains, making them limited for large space studies with such a specific thermal behaviour. The methodologies proposed in [18, 19, 20], basing on data driven approach, reproduce accurately the indoor thermal behaviour of the space, but they require a fine-grained instrumentation measuring for long period. This aspect makes such approach difficult to apply inside large spaces, taking into account the use and layout of it, which are barriers for sensors deployment.

1.3 Proposed solution

Given the literature analysis illustrated in the previous section, this thesis investigates and demonstrates a methodology for optimal sensor placement based two main stages: thermal characterization of the space and sensor network optimization. The climate characterization of the environment is based on the sub-zonal breakdown of a large space. The entire volume is horizontally divided in a sub-volumes, aiming to simulate or measure the hourly temperature trends in each of them. Different approaches are allowed as simulation modelling or field sensors for restrict data-driven or a combination of the previous two, in order to obtain a calibrated sub-zonal model of the space. An upgraded version of a well-mixed multi-zone modelling tool, known as HAMBase [22] was developed to permit the simulation based approach. In case of data driven approach, the deployment of the sensors has to characterize the horizontal air temperature distribution of the space to identify its main climate characteristic, allowing sensor placement optimization. A third approach, based on sub-zonal model calibration, was developed to generate high quality temperature distributions improving the accuracy of the optimization outcomes. The goal of the proposed methodologies for climate characterization of the space is to provide an intermediate approach, which reduces complexity and costs included on CFD, avoids the extensive sensors deployment and cost found on the data driven approaches and can take advantages from the zonal model approach.

Regarding the second stage, optimization, looking the outcomes form the analysis on the proposed state of the art, it should be underlined that a sensor network can be optimized using different criteria depending on the final goal of each proposed methodology, highlighting the lack of a unique recognised criteria. The final goal of this study was to develop a methodology to optimize the design of a sensor network for indoor air temperature monitoring though holistic criteria, which are based on the minimum sensors number that minimizes the measurement uncertainty, evaluating its impact on the indoor thermal comfort and operation costs (energy consumptions due to HVAC operation and cost of use of additional sensors). The developed methodology includes the application of a novel approach based on a measurement performance index, sum of statistical features, applied to the measurement deviation due to sensor placement. This approach can be considered unique, compared with the studies reported in Tab. 1.1, as it is focused on improving the measurement accuracy linked with positions and number of sensors. The optimization continues performing a sensitivity analysis evaluating the impact of the measurement uncertainty of the indoor air temperature, due to sensors position, on the indoor comfort level and energy consumption due to HVAC operation. The objective is to provide a methodology modular, able to cover most of the solution founded in the state of art, providing novelty trough the measurement performance index development.

1.4 Thesis outlines

The work presented in this thesis was firstly launched in [23], where a first step of the current methodology was made and included on a tool prototype called Sensor Optimization Unit (SOU). This tool was based on a user interface for data input, thermodynamic simulation of the space and a Genetic Algorithm as core of the optimization process. This thesis presents the development of an updated version of the SOU, the current methodology used the previous one as base. The work done in this thesis and in [23] is part of the FP7 EU project $SportE^2$ [24] that developed a scalable and modular BMS (Building Management System) dedicated to sports and recreational buildings. Sport facilities are unique by their physical nature, energy consumption profiles, the usage patterns of people inside, ownership, and comfort requirements, so a dedicated BMS is needed. $SportE^2$ BMS includes four modules providing smart metering, integrated control, optimal decision-making and multi-facility management. The smart metering system objectives are to monitor the energy performance of the whole building [25] and to characterize the building services operation [3]. The SOU was developed in order to optimize the design of part of the HOW module; in particular, the tool was applied to selected

large spaces to optimize the indoor air temperature monitoring. The increased accuracy on the temperature data were used by control and optimization modules to increase the facility efficiency in terms of thermal comfort and energy consumption. Three different papers are then reported, which were published during the project, to underline the importance of air temperature accuracy on developing optimal HVAC control strategies. The work proposed in [26] showed how the $SportE^2$ optimization system can support building managers in implementing energy efficient optimization plans. The study reported in [27] proved that the same optimization system was able to both predict and optimize energy consumption and thermal comfort inside an indoor swimming pool. The proposed study showed as an ANN (Artificial Neural Network) was used to run in near-real time an optimization algorithm to provide optimal HVAC set-points to maximize indoor thermal comfort with the minimum energy consumption. It should be underlined that the environmental conditions were retrieved from a sensor network installed in a swimming pool and the SOU was used to optimize its design, in order to increase the measurement accuracy of the air temperature, which was a key parameter to calculate a calibrated thermal comfort index used by the optimization module. Considering that the air temperature is one of the most influential variable on the comfort evaluation inside sports environments [2] and considering the state of art reported in the previous paragraphs, the level of accuracy of the air temperature measurement is a crucial task to address, in order to achieve fine climate control operated by HVAC systems, leading to objectives such as energy efficiency and maximization of the comfort level, as done by the BMS developed in $SportE^2$.
Taking into account the outcomes reported previously, the importance of the measurement accuracy on the environmental climate control chain was proved. Thus, a dedicated methodology is needed to investigate how the sensor network design can be optimized to achieve the maximum measurement accuracy with the minimum number of sensors deployed, evaluating the impact on thermal comfort and HVAC energy consumption.

This thesis presents the development, application and validation in real cases studies of the developed methodology to address that issue. The finalization of the study, presented in this thesis, was performed during a six months research experience with the IRUSE (Informatics Research Unit For Sustainable Engineering) research group in Galway, Ireland, from April 2015 to September 2015. The hosting building of the faculty was the Engineering Building NUI Galway, which is equipped with a BMS and an extensive set of sensors capturing environmental, energy and structural characteristics of the building. Air temperature data, gathered from sensors installed inside an open space office of the Engineer Building, were used as test case for the SOU optimization algorithm application.

The entire methodology is described starting from Chapter 2, where the approach is summarized in total and the main characteristics are underlined in order to clarify the proposed solution for the optimal sensor placement. Chapter 3 presents the thermal characterization of the space; in particular the section describes the approaches allowed by this methodology for the dataset generation process. Chapter 4 contains the description of the optimization process used to optimize the sensor network design. The application and validation of the entire methodology is performed in three different test cases and it is fully described in Chapter 5.

Chapter 2

General approach and methodology applied

This thesis proposes a methodology based on a novel measurement performance index to optimize the temperature monitoring in large spaces. The final outcome is the optimal number of the sensors and installation coordinates inside the environment. The entire methodology can be divided in two main steps:

1. An approach based on simulation, measurement or hybrid, generates a dataset representing the horizontal air temperature distribution inside the space; the previous chapter identified it as the key climate condition from large spaces, which needs to be captured for the optimization task;

2. An optimization solver uses the dataset generated in step 1 to optimize the sensor network design, in terms of number of sensors and placement along the perimeter of the space under study; the optimization first evaluates the measurement accuracy due to sensor position and then its impact on thermal comfort and HVAC operational cost.

The first one is described in Fig. 2.1 and it can be approached through three different ways: simulation, measurement or hybrid, a simulation model calibrated with measurements. The simulation approach is based on a sub-zonal model of the space, which divides the entire volume horizontally in equals sub-volumes, where the air can be considered perfectly mixed. A dedicated graphical user interface (GUI) was developed to guide the user through the data implementation process for the building, in order to run the simulation. Once the GUI (Appendix A) is filled, the software starts to build the sub-zonal model of the space and automatically calculates the needed number and positions of sub-zones. The process depends on numerical requirements, which are defined by the solver behind the simulation. The simulation outputs are hourly temperature trends for each sub-volume reaching a maximum period of one year. These time series represent the temperature values of each central node of each air sub-volume, considered perfectly mixed. The data-set generation based on measurement requires the installation of a temporary sensor

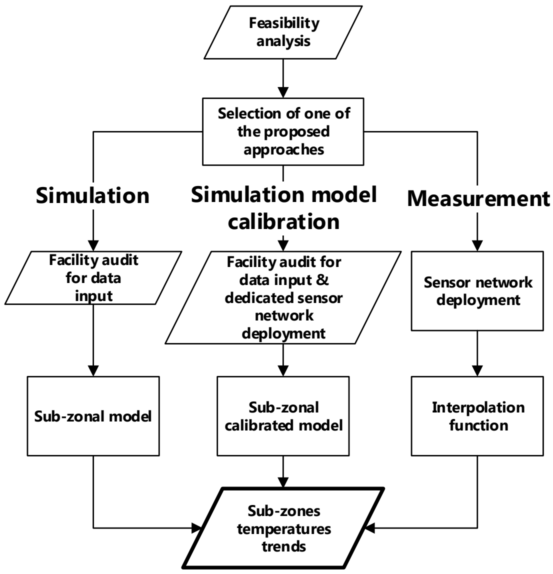


Figure 2.1: Dataset genaration approaches allowed by the SOU

network. First the space is virtually divided in sub-volumes, which are horizontally distributed in equal manner. The deployment process of the sensors has to guarantee that each sub-volume holds at least one temperature sensor; the number of nodes to be installed in each sub-volumes depends also on their dimension, taking into account that the sensors have to be deployed along the perimeter (due to large space layout constrains). As for the previous approach, the objective is to obtain temperature trends on the central points of the virtual sub-volumes; so a dedicated interpolation function, based on the weighted inverse distance method, was developed to obtain the final dataset useful for the optimization process. In case of simulation model calibration, a facility audit allows to collect data generating a sub-zonal model of the space following the approach presented above and a sensor network installation is mandatory as well; the selected measurement equipment should be deployed to capture the indoor thermal condition, but additional sensors need to be installed outdoor, in order to monitor the external climate conditions. This third approach is a combination of the previous two. A dedicated calibration process was developed to generate high quality indoor air temperature trends allowing most accurate optimization of sensor network design.

The generated temperature trends are used by the optimization solver of the SOU. The optimization workflow is composed by two consecutive steps, the first one (Fig. 2.2) provides the optimal sensors number and placement based just on measurement performance criteria. The second one (Fig. 2.3) generates

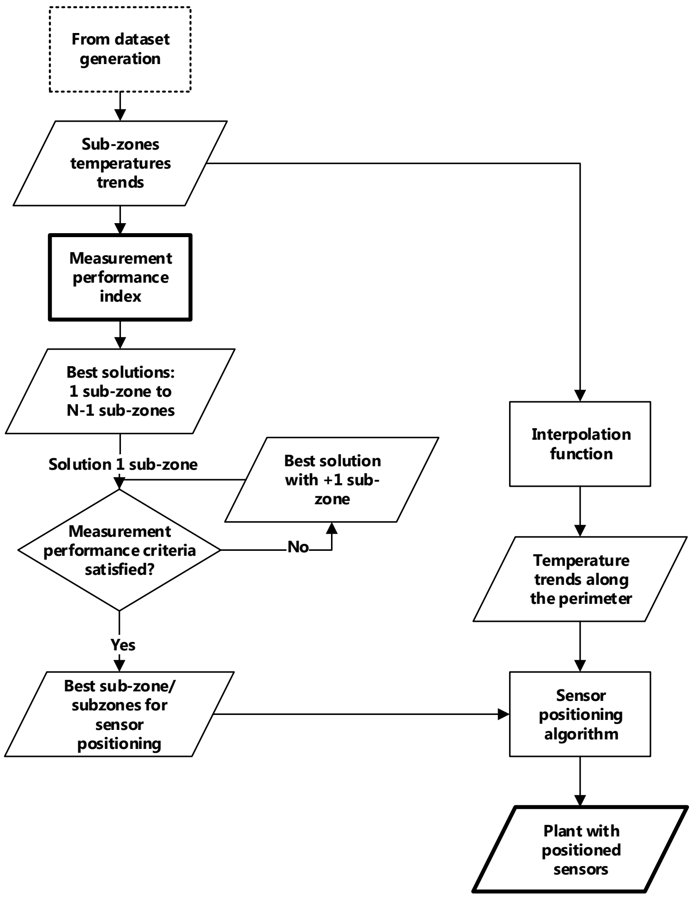


Figure 2.2: Optimization workflow based on measurement performance index

a trade-off between measurement accuracy (number fo sensors), taken from the previous step, and impacts on indoor thermal comfort and energy consumption due to HVAC operation. In both optimization procedures, the provided output is the space plant with the sensors nodes placed in optimal perimeter locations. The first step of optimization takes the simulated or measured temperatures trends coming from the sub-volumes dividing the space (Fig. 2.4). Thus, the mean of these trends is calculated and defined as reference temperature, which is referred as the best accuracy available for the air temperature monitoring inside the entire air volume, considered as perfectly mixed. The objective of the optimization is to define the minimum sensors number to achieve the minimum deviation from the reference temperature. As next step, the optimization

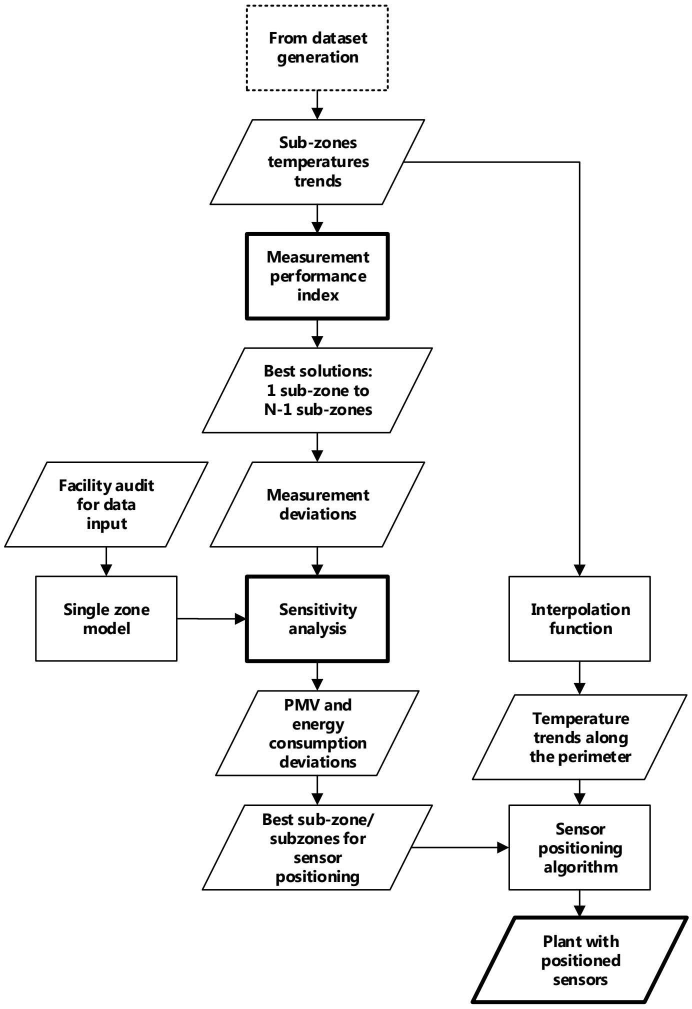


Figure 2.3: Optimization workflow based on trade-off between number of sensors, thermal comfort and HVAC energy consumption deviations

solver calculates the mean temperature trends by combining all the sub-zones trends, retrieved from the dataset generated from the previous step. The op-

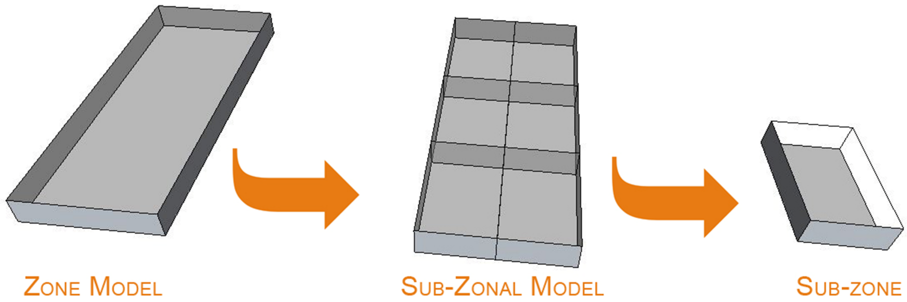


Figure 2.4: From zonal model to sub-zonal model

timization process continues calculating the deviances between the reference temperature trend and each trend obtained as combination between sub-zones. The deviances trends represent the measurement bias due to sub-zones selection to solve the temperature monitoring issue. Each deviance is assigned to the sub-zones selected as possible optimal solution. The optimization process proceeds applying a measurement performance index to each deviance trend. This index is made of a sum of statistical feature, which is the key novelty of the proposed approach. Specifically, each statistical feature evaluates the measurement error in terms of:

- Mean deviation, referred as the tendency to over/under estimate the average temperature of the entire space. An absolute low value of mean deviation prevents waste of energy and discomfort brought by overheating/overcooling;
- Standard Deviation, which represents the final measurement uncertainty. This feature is fundamental for thermal comfort evaluation and optimal HVAC system regulation;
- Outliers, defined as the amount of time spent by the monitoring system measuring outside the sensor uncertainty value, which is usually provided by the manufacturer;
- Z test, quantifying the effect of external perturbations on the measure.

Once the performance index is calculated for each deviance, it represents a quality index for each combination of sub-zones selected as potential optimal solution for sensor deployment. The solutions (deviances) are ranked basing on the index values calculated in the previous step. The first optimization step's objective is to select the optimal sub-zones where the sensor should be installed, in order to provide the required measurement performance, established by pre-defined criteria. The final position of installation for the sensor inside each sub-zone, selected as optimal, is then provided through the application of a dedicated positioning algorithm. A deeper analysis is done trough the second step of optimization. It proceeds generating a single zone model of the space, which outputs hourly values of predictive mean vote (PMV) and energy consumption due to heating/cooling system covering a maximum period of one year. The deviances, retrieved from the previous optimization step due to the different optimal sub-zones configurations, were used to perform a sensitivity analysis on the single zone model to evaluate the impact of measurement accuracy (number of sensors) on both indoor thermal comfort level and energy consumption. The optimization process was divided in two steps, aiming to allow a modular approach for the sensor optimization task depending on the user needs and cost constraint. In fact, the second stage of optimization needs the development of an additional simulation model of the space and a sensitivity analysis based on calibrated algorithms.

Chapter 3

Dataset generation

3.1 General approach

In the previous chapter the objective, the needed inputs, the optimization approaches of the SOU were introduced to show a general picture of the software. This chapter will describe in details the approaches allowed by the SOU for the dataset generation. The objective is to generate the necessary datasets used as inputs by the optimization algorithms of the SOU to calculate the optimal design of the sensor network in terms of minimum number of sensors and relative placement.

3.2 Simulation

The objective is to have a simulation model able to characterize the indoor horizontal air temperature distribution of a large space at a certain heigh level (typical height of installation for a thermostat). The thermal behaviour of large spaces is highly influenced by external and internal factors. External factors are the outdoor weather conditions, as direct and diffuse solar radiation, external air temperature and relative humidity, wind direction and velocity, influence of adjacent rooms, external shadowing elements. Otherwise, thermal properties of the envelope, glazing surfaces properties, building orientation, use profile of the space, spatial and temporal characterization of the internal loads, characterization of local HVAC, primary systems and control strategies are the main indoor factors influencing the indoor air temperature distribution. A thermal modelling aiming to relate the space heat, air and moisture influence on the temperature distribution has to include the possibility to simulate the factors mentioned above.
A dedicated thermal modelling was developed for the discretization of the horizontal air distribution of the space, simulating a dataset of the temperature distributions. The thermal model is based on the HAMBase library, that is an open library implemented in Matlab computing environment [28], which

is useful for code customization purpose. It simulates the hourly indoor air temperature and humidity of a multi–zone building with a relatively small mathematical computational requirement. De Wit described extensively the physics of this model in [22].
The multi-zone model approach of the HAMBase is not accurate enough to simulate the temperature distribution of a large space in a building, because this approach calculates one air temperature value per hour that represents the average temperature value inside the whole space; in fact, the HAMBase does not allow the spatial discretization of the mentioned factors influencing the horizontal temperature distribution. The sub-zonal approach can overcome the lack of resolution of the multi-zone approach. The HAMBase library was then customized to develop a sub-zonal model from the multi-zone one. The updated version of the multi-zone model divides the space, which would normally be a single zone, into a coarse network of smaller sub-zones, as shown in Fig. 2.4. Each sub-zone has to satisfy the hygro-thermal and the inter-zonal airflow models, then the air contained inside each sub-zone, dividing the single zone, is assumed to be perfectly mixed. The sub-zonal approach permits to increase the resolution of the air temperature distribution on a virtual horizontal plane of the space. The updated model is able to generate the dataset of temperatures requested by the optimization solver.
The new sub-zonal model represents the sensor network and simulates the value of air temperature of each sub-zone covering a period of one year with a fixed time step. The simplified approach of the proposed tool allows the problem set-up with low computational load for a user that has no specific technical expertise (as required for a CFD). It also allows to simulate the thermal behaviour of an environment during one-year period, taking into account the environment weekly use profile, the influence of adjacent rooms, internal loads distribution in space and time, external weather conditions and external shadowing elements, that impact significantly on the temperature distribution.
Since that the developed thermal model is a modified version of HAMBase, several parameters were added to the ones already needed by the original tool and the existent documentation is not enough to run the simulation. Moreover the tool presented in this thesis is meant to be used by HVAC engineer, who are not simulation expert, so a dedicated (GUI) was developed guiding the end-user from the dataset generation process to the optimization goal. It contains the total amount of the necessary inputs to run the simulation plus optimization process. The basic idea behind the GUI is to make the tool user-friendly, so a certain amount of parameters are automatically derived and implemented during the GUI filling phase.

3.3 Measurement

The data driven approach is based on field measurement coupled with an interpolation algorithm. The entire volume of the space is virtually divided in horizontal sub-volumes, equally distributed in the space. The virtual division follows the one generated by the sub-zonal approach. Then, at least one sensor has be installed inside each sub-volume, acquiring temperature data for a certain period, sufficient to capture the typical usage profile. The sensors should be installed at typical thermostat height above the floor, along the space perimeter and near the occupied zone. It is fundamental to collect information about the room usage, which has a strong influence on the indoor temperature distribution. Finally, the gathered data are processed by an interpolation algorithm to generate temperature trends that correspond to the value of the temperature in the central point of the virtual sub-volume, dividing the entire space. The sensors should not be installed where:

- there are unusual heating conditions, such as: direct sunlight, near lamps, radio, TV screens, near hot water pipes in a wall;
- there are unusual cooling conditions, such as: in a draft from a stairwell, door, or window;
- air circulation is poor, such as: in a corner, an alcove, behind an open door.

3.4 Simulation model calibration

Model calibration means a data-driven process that leads to the optimal values of the model parameters, allowing the model to simulate the output closest as possible to the measured one. The calibration activity can be manual by direct tuning the model parameters, until the comparison between output and measurements reach the desirable uncertainty. The developed methodology is a quasi-automated calibration procedure due to few operations that still need user interaction. The following list contains the requirements that were fulfilled to develop the model calibration process:

1. Selection of the model parameters that need to be calibrated;
2. Build a robust and effective optimization process able to find the best set of parameters values;
3. Dedicated measurement procedure to retrieve the needed data from the field, fundamental for the model calibration process.

3.4.1 Requirements for problem solving

The first step to build a robust calibration method was the selection of the most influencing input parameters for the model, which the calibration process should focus on. In [29] the effect of uncertainties of a selected group of the HAMbase input parameters were investigated and the simulation model resulted most sensitive to changes in insulation material layer thickness, ventilation rate, and the internal surface heat transfer resistance.
Starting from that, the number of parameters under study was increased basing on the experience and knowledge made during the developing and usage phase of the thermal model. This process brought to a selection of a group of parameters reported in the following Tab. 3.1.

Parameter	**Short-Unit**	**Range**
Interzonal airflow	Linkv $[m^3/s]$	$\pm 20[\%]$
Casual heat gains	Qint $[W]$	$\pm 50[\%]$
Water vapour sources	Gint $[Kg/s]$	$\pm 50[\%]$
Air changes	Vmin $[1/h]$	$\pm 50[\%]$
U-value transparent surfaces	Uglas$[W/m^2K]$	$\pm 20[\%]$
Solar gain factor	ZTA$[-]$	$\pm 20[\%]$
Material layer thickness	D $[m]$	$\pm 20[\%]$
Internal surface heat transfer resistance	Ri $[Km^2/W]$	$\pm 20[\%]$
Convection factor of the heating system	CFh $[-]$	$\pm 20[\%]$
Heating system time constant	Tau $[h]$	$[0;1]$
Heating capacity	P $[W]$	$\pm 20[\%]$
Inlet factor	If $[-]$	$[0;1]$
Solar factor	Sf $[-]$	$[0;1]$

Table 3.1: Thermal model parameters

The range column of the Tab. 3.1 represents the upper and lower bounds of freedom for the parameters values. The bounds are expressed in percentage of the initial guess of the parameters, which represents the initial values of them considered as starting point for the optimization process. Some of the parameters (Tau, If, Sf) can just assume a value between zero and one. In case the room is still in design stage, some of these data can be extract from the project itself. In case of retrofitting of an existing room, the calculus and definition of them could be a challenge.

A dedicated audit procedure for the space has to be performed. The objective of the audit is to obtain the necessary data to run the simulation model though geometrical characterization of the space, the identification of the internal heating/cooling sources, characterization of heating/cooling system and weekly scheduling usage of the space. Since that the parameters contained in

Tab. 3.1 are affected by high level of uncertainty, cause difficult to evaluate and measure. The calibration modelling process allows to evaluate them in a most accurate way. The selection of the range of freedom for the parameters is mostly based on the experience matured during the development and application phases of the thermal model.

3.4.2 Optimization process for calibration

A detailed review of methods to match building energy simulation models to measured data is reported in [30], the paper reports an overview of the current approaches for model development and calibration. In [30] an extended comparison between calibration modelling approaches for predicting building energy performance is reported. Kramer in [31] developed an optimization routine to fit the output of simplified hygro-thermal building model in state space form of the HAMbase with measured data. The optimization process described in [31] was developed in Matlab, as the tool presented in this thesis, and it has been proved to be robust. Those conditions were considered sufficient to select the mentioned approach as base of the optimization process proposed in this thesis. The next paragraphs will describe how that methodology was modified to fulfil the goal of this study. Two solvers mainly compose the optimization process: the first one is based on Genetic Algorithm (GA) [32], the second one on Pattern Search (PS) method. In [31] the author underlined as "GA has proved to be a very promising in finding a near optimal solution in very big solution spaces", so the first step of the optimization will provide a quick near optimal solution for the parameters. Therefore, the genetic approach is used. GA is one of the most powerful heuristic method to solve optimization problems [33]. In particular the algorithm used in this study, it is implemented inside the Matlab optimization toolbox by default and fully described in [34].

The optimization process is represented in Fig. 3.1, where it can be seen as the optimization process start from the definition of a first guess of parameters values and their upper/lower bounces. These parameters are the inputs for the thermal model that produce the first temperatures map. The fitness function evaluates the quality of the solution through comparison between measured and simulated data. If the quality of the solution is not enough, the optimization process continues through the genetic algorithm that produces another set of possible solution for the parameters. These solutions are sent to the thermal model, which produces outputs and the process iterates until the stopping criteria are satisfied: deviance between measured and simulated outputs equal to 0.1 or the number of iterations reached the maximum value of 100. The set of parameters that satisfied the stopping criteria is considered as the optimal set and the first stage of optimization can be considered concluded.

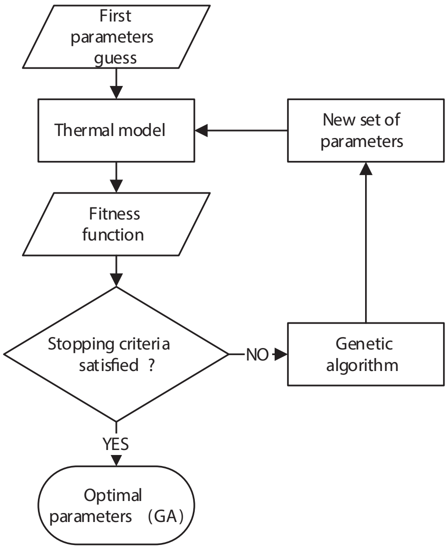


Figure 3.1: First optimization stage using Genetic Algorithm

The second stage is based on the pattern-search algorithm, also implemented inside the Matlab optimization toolbox [34]. As reported in [31],"the Pattern Search algorithm is a gradient free, deterministic algorithm, very suitable for not smooth and discontinuous problems".

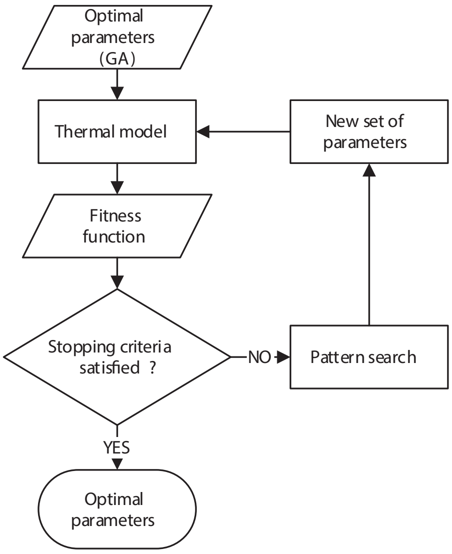


Figure 3.2: Final optimization stage using Pattern Search algorithm

Starting for the solution provided by the GA on the first stage, the PS [34] polls solution points around the starting one, the solution that improves the fitness function becomes the new starting point. The process continues until the stopping criteria are reached: solution accuracy equal to 0.1 or maximum number of iterations equal to 1000. The Pattern-search algorithm defines the global solution, in other words the final values of the parameters (Fig. 3.2). Others optimization algorithms as multi-starting point, particle swarm optimization were taken into account. The selection of the described workflow was made based on comparison of performances with them, in terms of quality of fitness function evaluation and time-consuming point of view.

3.4.3 Fitness function

In general, an optimization process needs the design of a dedicated fitness function. Given a particular solution (set of parameters), the fitness function returns a single numerical value, or "figure of merit", which is supposed to be proportional to the "utility" or "ability" of the solution. The objective of the optimization is to provide a set of parameter able to reproduce the maps of the air temperature distribution in the space, for the point of view of absolute temperature values inside the sub-zones and temperature gradients between them. Where the sub-zone is represented as one temperature node in the centre of the volume, considered as well mixed. The fitness function takes as inputs the measured (Eq. 3.1) and simulated (Eq. 3.2) temperatures expressed as following:

$$T_m = \begin{vmatrix} T_{m_{1,1}} & \dots & T_{m_{1,N}} \\ \vdots & \ddots & \vdots \\ T_{m_{H,1}} & \dots & T_{m_{H,N}} \end{vmatrix} \tag{3.1}$$

$$T_s = \begin{vmatrix} T_{s_{1,1}} & \dots & T_{s_{1,N}} \\ \vdots & \ddots & \vdots \\ T_{s_{H,1}} & \dots & T_{s_{H,N}} \end{vmatrix} \tag{3.2}$$

Where N represents the number of sub-zones (matrix columns) and H the number of hours (matrix rows) for a maximum of 8760 (one year). First the fitness function calculates the deviances between measured and simulated temperatures for each sub-zone as following (Eq. 3.3):

$$\begin{aligned} \Delta_{1,1} &= T_{m(1\mapsto H,1)} - T_{s(1\mapsto H,1)} \\ &\vdots \\ \Delta_{N,N} &= T_{m(1\mapsto H,1)} - T_{s(1\mapsto H,1)} \end{aligned} \tag{3.3}$$

Then calculates the temperature gradients between each possible sub-zones couples for the measured (Eq. 3.4) and simulated ones (Eq. 3.5) in a separated way as following:

$$\begin{aligned} \Delta_{m(1,2)} &= T_{m(1 \mapsto H,1)} - T_{m(1 \mapsto H,2)} \\ &\vdots \\ \Delta_{m(N-1,N)} &= T_{m(1 \mapsto H,N-1)} - T_{m(1 \mapsto H,N)} \end{aligned} \tag{3.4}$$

$$\begin{aligned} \Delta_{s(1,2)} &= T_{s(1 \mapsto H,1)} - T_{s(1 \mapsto H,2)} \\ &\vdots \\ \Delta_{s(N-1,N)} &= T_{s(1 \mapsto H,N-1)} - T_{s(1 \mapsto H,N)} \end{aligned} \tag{3.5}$$

The next step is the calculus of the deviances between measured (Eq. 3.4) and simulated (Eq. 3.5) gradients as following (Eq. 3.6):

$$\begin{aligned} \Delta_{1,2} &= \Delta_{m(1,2)} - \Delta_{s(1,2)} \\ &\vdots \\ \Delta_{N-1,N} &= \Delta_{m(N-1,N)} - \Delta_{s(N-1,N)} \end{aligned} \tag{3.6}$$

Then the fitness function apply the Root Main Square Error ($RMSE$) operator to each delta calculated previously as following (Eq. 3.7):

$$\begin{aligned} RMSE_{1,1} &= \sqrt{\frac{1}{n}\sum \Delta_{1,1}^2} \\ &\vdots \\ RMSE_{N,N} &= \sqrt{\frac{1}{n}\sum \Delta_{2,2}^2} \\ &\vdots \\ RMSE_{1,2} &= \sqrt{\frac{1}{n}\sum \Delta_{1,2}^2} \\ &\vdots \\ RMSE_{N-1,N} &= \sqrt{\frac{1}{n}\sum \Delta_{N-1,N}^2} \end{aligned} \tag{3.7}$$

The goodness of each solution is given by the minimization of the following equation (Eq. 3.8):

$$
\begin{aligned}
Fitness = \; & w_1 * (\frac{1}{n}\sum(RMSE_{1,1} + \ldots + RMSE_{N,N}) \\
& + w_2 * (\frac{1}{n}\sum(RMSE_{1,2} + \ldots + RMSE_{N-1,N})
\end{aligned} \tag{3.8}
$$

Where w1 and w2 are weighted factors useful to customize the optimization process. The first term of the equation represents the deviance between measured and simulated temperatures relative to the same sub-zones. The second term represents the deviance between measured and simulated temperatures, calculated as gradients between different sub-zones. The different algorithms run minimizing this function and the process continues until stopping criteria are reached. The criteria are two, the first is called stall, when the fitness function values is less than function tolerance (1e-1); while the second one appears when the algorithm reach a pre-defined maximum number of iterations (100 in case if GA and 1000 in case of PS).

3.4.4 Measurement data for model calibration

The necessary condition of a calibration modelling process is the knowledge of the output and modelling the physics of the system under study in the most accurate way. In this case, the output are measured data, which represent the indoor air temperatures values for the different sub-zones, which it has been divided the space. While, to model the indoor environmental conditions in a correct way, accurate data regarding the outdoor conditions are mandatory. The simulation uses as external inputs a meteofile of hourly weather data including some data of the location as latitude, longitude, time zone and albedo of the site. The file must start at 1 January and should have at maximum 365 days. A longer period than 365 days can be simulated but then the year is repeated. In leap years the last day is used twice. The meteofile contains parameters as year, diffuse solar radiation, 10*exterior air temperature, Direct solar radiation (plane normal to the direction), cloud cover(1...8), 100*relative humidity outside, 10*wind velocity, wind direction. Then hourly meteofiles of an average year can be generated with the program METEONORM [35]. The meteo file data can be downloaded using the SOU user interface through the website [36]. To build an effective calibration method the external conditions should correspond to the real measured one inside the space, during the same monitoring period. Since that the data about the indoor temperature distribution can be retrieved installing the sensor nodes inside the space to be used as output, external sensors are also requested. So, the installation of a meteo station outside the facility is recommended, but it can be not cost effective for sensor network optimization purpose. The idea is to install sensors for air temperature and relative humidity external monitoring and then ,since that, the direct and diffuse solar radiation is one of the most influential external parameter, in case the data is not available, it can be retrieved with a sufficient accuracy using a methodology fully described in [37]. The developed algorithm was implemented in this study, allowing to calculate the diffusive and direct solar radiation from external air temperature and relative humidity trends. The time window of measurement campaign should be enough to cover the seasonal thermal characterization of the environment; the acquisition rate should be equal to a minimum value that allows a correct digitalization of the phenomena under study.

3.4.5 Sub-zonal model calibration

The indoor temperatures, available from the installation of the sensor network, are gathered into daily groups, maintaining hourly sampling. The groups are further filtered keeping just hourly temperature profiles during the HVAC operational hours. The filtered data are processed by cross-correlation selection criteria. The output of the selection process has to lead to a minimum number of 10 folds [41] of daily trends that reported mutually high correlation values. This sub-group of the initial one represents the indoor thermal behaviour for the room. The selected data are divided in 10 folds for further analysis using a cross-validation method, but for the model calibration process the entire amount of selected data is used.
In the meanwhile, a detailed facility audit allows the generation of a basic subzonal model. Then, the filtered data and the basic simulation model become the fundamental part of the model calibration process. The process of model calibration starts working iteratively through the optimization algorithms and the fitness function, deeply described in previous sections. The fitness function evaluates the quality of parameters using simulation and all the filtered data from measurement. The calibration drives to the definition of optimal values of thermal model parameters. The calibrated model is used to simulate the indoor air temperature inside each sub-zones dividing virtually the environment, during the period under study: one month, an entire season, a year, depending on the goal of the optimization.

Chapter 4

Optimization solver of the SOU

4.1 General approach

The workflow of the tool was presented in Fig. 2.1, 2.2, 2.3 and the previous chapters described the different approaches used to characterize the indoor environmental condition inside the space under study, generating hourly sub-zones air temperature trends. The optimization objective is to use these temperatures trends to design an optimal sensor network in terms of number of sensors and placement. The optimization task was divided in two steps to provide a most comprehensive supporting tool for HVAC engineer during the environmental monitoring design stage. In order to give a general picture of the different optimization stages, Tab. 4.1 summarized on the first three rows the requirements for each optimization stage based on the dataset generation approach, then the last row describes the different outcomes from each optimization stage.

Table 4.1: tab:Optimization stages requirements and outputs

	Measurement performance evaluation	**Sensitivity analisys**
Simulation	Sub-zonal model	1- Single zone model 2- Sensitivity analysis
Measurement	Sensor network	1- Single zone model 2- Sensitivity analysis
Calibrated simulation	1- Sub-zonal model 2- Sensor network	1- Single zone model 2- Sensitivity analysis
Optimization output	Number of sensors and position base on measurement accuracy	Number of sensors and position based on measurement accuracy, impact on comfort and energy consumptions

4.2 Measurement performance evaluation

The final optimization objective is the minimization of sensors number able to provide the minimum deviation from the measurement performed by reference condition, at least one sensor in each sub-zone, which virtually divides the space. To this aim, the optimization solver receives the temperatures dataset, as shown in Fig. 2.2, evaluates the measurement performances of proposed sub-zones temperature trends combinations, in terms of numbers and positions against the reference temperature, which represents the uncertainty due to the sensors positioning and determines the optimal sub-zones for the sensors installation.
The SOU thermal characterization provides indoor temperature trends used to define the maximum measurement accuracy achievable (reference condition), which is the temperature calculated as the mean value of the temperatures evaluated in the sub-zones. Then, the software calculates the deviation between the reference temperature trend from the previous step and temperature trends derived by combinations of reduced sub-zones temperature trends. The optimization solver evaluates the measuring performance of each combination using a measurement performance index based on statistical features calculated on those deviations. In detail:

- The mean deviation that represents the distance from the reference condition; a mean value closer to zero corresponds to minor under or over estimation of the thermal conditions that could cause an overheating/overcooling or underheating/undercooling;
- The standard deviation, here considered with a coverage factor k=2, that is a measure of the deviation distribution around the mean value. Higher the standard deviation higher the uncertainty of the measurement;
- The outliers period, expressed in hours, that is a measure of the period where the standard deviation is higher than the sensor uncertainty (datasheet value), which is or will be installed to monitor the indoor temperature;
- The Z index, which represents the so-called z-statistic. It evaluates how close the deviation is to a Gaussian distribution. More Gaussian is the distribution, lower is the influence of perturbations on the measurement due to external factors.

Once that the performance index is calculated, a positioning algorithm defines the precise position of installation for each sensor node.
A deterministic solver determines the sub-zones where sensors should be placed. Starting from the number of sub-zones, a sensor is represented as a bit equal

to 1 if the sensor is installed inside the sub-zone and 0 if not. Each sub-zones configuration can be represented as a row vector, so it is a sequence of bits (0 or 1) whose length is given by the number of sub-zones as shown in Fig. 4.1. The deterministic solver generates all the possible solutions of installation (a

sub-zone 1	sub-zone 2	sub-zone 3	sub-zone 4	sub-zone 5	sub-zone 6
0	1	0	0	0	1

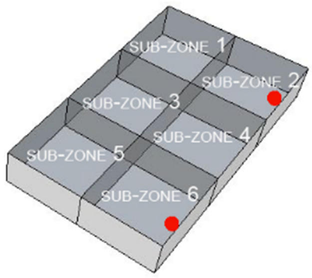


Figure 4.1: Sensor network representation as bit string

string of bit for each one), that are 2^{n-1} combinations of 0 and 1, where n is the total number of sub-zones. Then, the solver assigns a label to each row, represented by a number from 1 to 2^{n-1} (set), which will be used to identified the configuration of the solution of installation, along the entire optimization process. Each sub-zones combination is compared to the reference condition (a string of ones), which is a temperature profile T_r calculated as the mean value of the n sub-zones temperature profiles (Eq. 4.1):

$$T_r = \frac{\sum_{i=0}^{n} T_i}{n} \tag{4.1}$$

The metric of comparison for each combination (set) is the deviation (E_{set}) with respect to T_r and calculated as following:

$$E_{set} = T_{set} - T_r \tag{4.2}$$

Where T_{set} is each temperature profile of the 2^{n-1}, provided by the combination of sub-zones and calculated as the mean value of the temperature profiles of each sub-zone included in the combination. Once calculated the deviations E_{set} for all possible combinations, their statistical features, are evaluated. All the combinations are ranked (Tab. 4.2) according to each statistic and receive a score (S_z) equal to the position occupied in each ranking (R), in particular each score is calculates as $S_z(set) = (2^{n-1} - R)$, where $z = 1$ to 4 and S_1 is the score for the mean deviation, S_2 for the standard deviation, S_3 for the outliers and S_4 for the Z index. The sum of the scores, achieved in each ranking, provides

Table 4.2: Ranking deviances assignment process

set	**Ranking (R)**	**Mean deviation of each E_{set}**
15	1°	0.1 $°C$
34	2°	0.14 $°C$
...	...	...
2	2^{n-1}	1 $°C$
set	**Ranking (R)**	**Std deviation of each E_{set}**
17	1°	0.13 $°C$
42	2°	0.25 $°C$
...	...	...
1	2^{n-1}	1 $°C$
set	**Ranking (R)**	**Outliers of each E_{set}**
14	1°	1
55	2°	3
...	...	...
7	2^{n-1}	681
set	**Ranking (R)**	**Z index of each E_{set}**
25	1°	0.7
36	2°	1.2
...	...	...
2	2^{n-1}	9

the performance index (I_m) for all the monitoring configurations, calculated as following (Eq. 4.3):

$$I_m(set) = S_1(set) + S_2(set) + S_3(set) + S_4(set) \tag{4.3}$$

The output is a number 2^{n-1} of solutions with the respective performance index $I_m(set)$. Once that an I_m is assigned to each combination of sub-zones (set), the algorithm groups the solutions in terms of sub-zones number and selects each solution that achieved the best I_m in each group. The best sensors configuration, among the available, is the one that fulfils the defined criterion. The standard deviation, that represents the resulting measurement uncertainty due to sub-zones configuration, has to be lower or equal to the uncertainty of the sensor (from datasheet), which will be deployed or it is already installed in the sub-zone.

4.3 Sensitivity analysis

The first step of optimization calculates the best sensor network design in terms of number of sensors and position using a dedicated measured performance index, as explained in the previous section. A further investigation is needed to evaluate the impact of the measurement uncertainty on the indoor thermal comfort level and energy consumptions due to HVAC operation. This second step of optimization uses as inputs, from the previous step, the mean and standard deviations for each of the best sub-zones configurations based on the maximum I_m. Then it generates a normal distribution for each of the retrieved optimal sub-zones configurations. These normal distributions represent the measurement deviations for each solution from the reference condition. A single zone simulation model of the space has to be developed following the original simulation approach proposed by the HAMBase [22]. In case of thermal characterization of the space based on simulation approach or calibrated simulation approach, the needed parameters to build a single zone model can be retrieved from the sub-zonal one; while in case the dataset generation process is based on measurement, a dedicated facility audit has to be performed to obtain the needed parameters to build the single zone model.

The next step consists on the evaluation of the impact of the air temperature measurement deviations on comfort and energy efficiency, following the schema in Fig.4.2. Once that the single zone model is built, it produces as output sin-

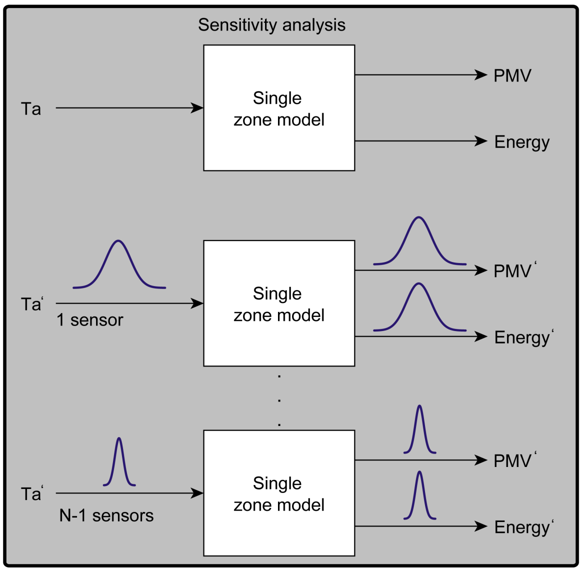


Figure 4.2: Sensitivity analysis SOU

gle hourly air temperature trend, which represents the mean temperature of the entire air volume of the space, considered as perfectly mixed. The HVAC control system uses the hourly air temperature as feedback to carry out the thermal regulation of the space. The air temperature trend is used by the single zone model to calculate the PMV value though a dedicated algorithm described in [2]. The simulation model is also providing hourly energy consumptions due to HVAC operation. First, the single zone model simulates an ideal indoor temperature trend (Ta), considering the feedback value for the HVAC not affected by measurement deviation. Then it calculates the PMV value and the Energy consumption. The effect of the measurement deviation of the hourly air temperature trend (Ta'), due to the sensors positions, on the PMV' and Energy consumption' values is evaluated trough a Monte Carlo method. Following the [38], the number of sampling (Ta') has to be equal to 10^6 expecting to deliver a 95% coverage interval for the output quantity. Where Ta' is equal to Ta plus the measurement deviation evaluated for each optimized sensors configuration retrieved by the optimization algorithm and expressed as normal distribution. The propagation of the measurement uncertainty generates a deviation on the model outputs. The comparison between the outputs coming from the first ideal model and the outputs, coming from the perturbed one, is expressed on deviation respect the original values and plotted related the number of sensors of the different solutions. The analysis of variances drives the process to the selection of the best sensor configuration for the monitoring system.

4.4 Sensor positioning algorithm

Once the sub-zones, where sensors should be installed, are identified by the first or second optimization methods, previously described, the precise location of installation for the sensor, inside the sub-zone, has to be delivered to the user. The nodal approach, adopted by the simulation model or measurement, considers the sub-zones as well mixed and the temperatures calculated are to be considered as the central temperatures in each sub-zone. An increase of spatial resolution is needed to define the deployment points for the sensors in the space. In fact, large spaces present constraints for network deployment and sensors cannot be placed in the centre, their deployment is usually restricted to the perimeter walls. The positioning algorithm provides the coordinates of installation of the sensor/sensors along the perimeter of the environment according to the sub-zones selected in the previous step. According to [39, 40], the perimeter temperatures values are calculated using an interpolation function based on the inverse distance weighting method [39] to obtain the necessary increase of temperature spatial resolution. The algorithm takes as inputs the temperature trends coming from the n sub-zones, the positions of these source points are fixed as central node (Fig. 4.3) for each sub-zone that composes the entire space. The temperatures at the destination points (points marked in black, along the perimeter of the sub-zone, Fig. 4.3) are estimated by a linear combination of the values at the source points. The output is a map that represents the horizontal temperature distribution along the perimeter. Finally, the sensors positioning process selects for each sub-zone the perimetral

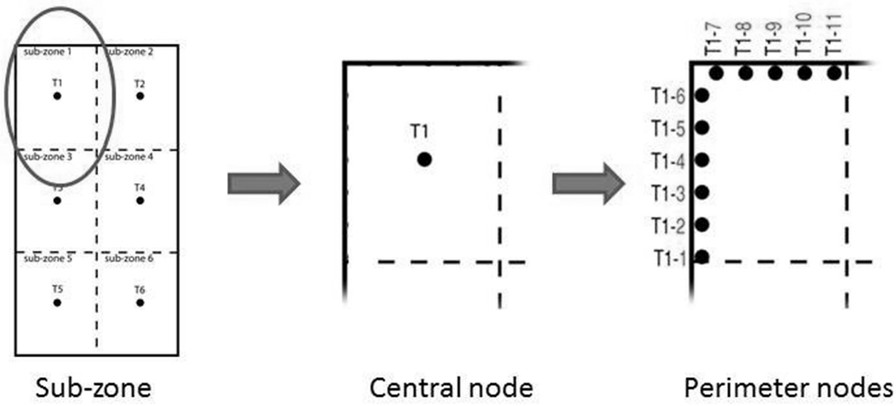


Figure 4.3: Sub-zone positioning algorithm

position that provides a temperature with the minimum root main square error (RMSE) with respect to the sub-zone central temperature.

4.5 Evaluation of model prediction accuracy

In general, Cross-Validation (CV) is a powerful technique used to evaluate or compare learning algorithms by dividing available data between training and validation sets. A detailed study about CV is reported in [41]. Here, CV is applied to evaluate how effective can be the developed calibration method on each case study, in terms of prediction accuracy on the sensor position. The idea behind the calibration method approach is to install a temporary sensor network in the case study, capturing the indoor and outdoor thermal behaviours for a restricted time window, then use the gathered data to calibrate the sub-zonal model and finally calculate the optimal solution of installation for the sensor network. So, future measurements will not be available to verify the consistency of the solution provided. The developed approach provides an additional information regarding the effectiveness of the calibration method in each case study, in terms of prediction of the optimal sensors position.
The k-fold cross-validation is applied to filtered data for the sub-zonal model calibration. This approach consists on k iterations of training and validation in a way that within each iteration a different fold of the data is held-out for validation, while the remaining k-folds are used for training the sub-zonal model. The validation cases are equal to the number of folds dividing the measured data. Each case is treated following the workflow described below. The developed procedure first selects the validation data. Then use the calibration data to tune the thermal model calculating the optimal parameters for it. The optimized sub-zonal model simulates the indoor temperature profiles for the validation day. The measured and simulated data are submitted to the optimization algorithm, described before, to calculate the optimal sensors positioning solutions. The validation consists on controlling the matching score between the solutions using simulated and measured data. Both solutions can be represented as a sequence of bits (0 or 1) whose length is given by the number of sub-zones dividing the space under study. For each test case of the k available two sequence of bits are compared following the classification criteria reported on Tab. 4.3. In particular, Tab. 4.3 reports an evaluation criteria

Table 4.3: Classification criteria of the cross-validation process

Predicted class - Actual class	**1**	**0**
1	True positive	False positive
0	False negative	True negative

mostly used on machine learning classification problem and called "precision and recall". The cited criteria is usually applied to classification problem to compare the performance of different algorithms, the proposed study is focusing on finding a measure of prediction capability of the sub-zonal model, generated through calibration model approach, described in subsection 3.4.5. The proposed classification matrix is applied comparing each pair of solutions coming for each of the k validation cases. Looking the Tab. 4.3, the predicted class is the simulated solution, while the actual class is the measured solution. The final results coming from the comparison of measured and predicted solutions is a matrix of 0 and 1, where 0 represents a False Positive or a False Negative, while 1 is a True positive or a True negative. The next example in Tab. 4.4, tries to clarify the classification process. Applying the evaluation

Table 4.4: Example of classification process

	Sub-zone 1	**Sub-zone 2**	**Sub-zone 3**	**Sub-zone 4**
Actual solution	0	1	0	0
Predicted solution	1	0	0	0
Verification	0	0	1	1
Classification	False positive	False negative	True negative	True negative
Total score = 2 of 4 (50%)				

criteria described in Tab.4.4 to the k cases, the validation process finally will get a percentage of score, which is considered as quality index to evaluate the prediction capability of the calibrated sub-zonal model.

Chapter 5

SOU application to cases study

The methodology presented in this thesis was applied to three different cases study. Since that the tool allows different approaches for sensor network optimization, each of the selected case study was used to apply the different dataset generation options and optimization steps. In particular the first test case is an indoor swimming pool which was a pilot case inside the $SportE^2$ project; the test case was used to apply and validate the dataset generation phase based on measurement and simulation approach. The second test case is a fitness room that also was a pilot case on the $SportE^2$ project; the test case was used to apply the dataset generation approach based on calibrated simulation, then the application of the entire optimization methodology is presented and the accuracy of the prediction is evaluated. The third test case is an open office placed on the Engineer Building NUI Galway; the building has an high level of automation, a huge number of sensors are installed inside the building and a Building Management System (BMS) apply fine control strategies alternating natural and mechanical ventilation though use of HVAC and automated windowed facade. Since the building is equipped with such an high level of automation and a sensor network for continuous environmental monitoring, the data driven approach for thermal characterization of the space was applied, then the application of the optimization based on measurement performance evaluation is presented.

5.1 Case study 1

5.1.1 Description of the environment used as case study

The SOU is a tool conceived to find the optimal temperature sensors positioning in large spaces, where the building orientation, the solar radiation and the quantity of glazed surface, adjacent buildings, shadowing elements assume a fundamental role for characterize the thermal behaviour of the space. The swimming pool area of Fidia sports center, sited in Cesano (Rome) (Fig. 5.1) present all those attributes. The main dimensions of the space are 35 m width and 16.5 m depth, the roof is gable with the maximum height of 6 m. There are two swimming pools: adult pool with a surface of 312.5 m2, children pool of 75 m2, the external walls facing to North, East and South are mostly glazed surfaces and the wall facing to West is an internal wall of wood (8 cm) shared with changing rooms. A dedicated biomass boiler is used to heat pool water, pool air and shower water and a gas boiler is used as auxiliary. As shown in

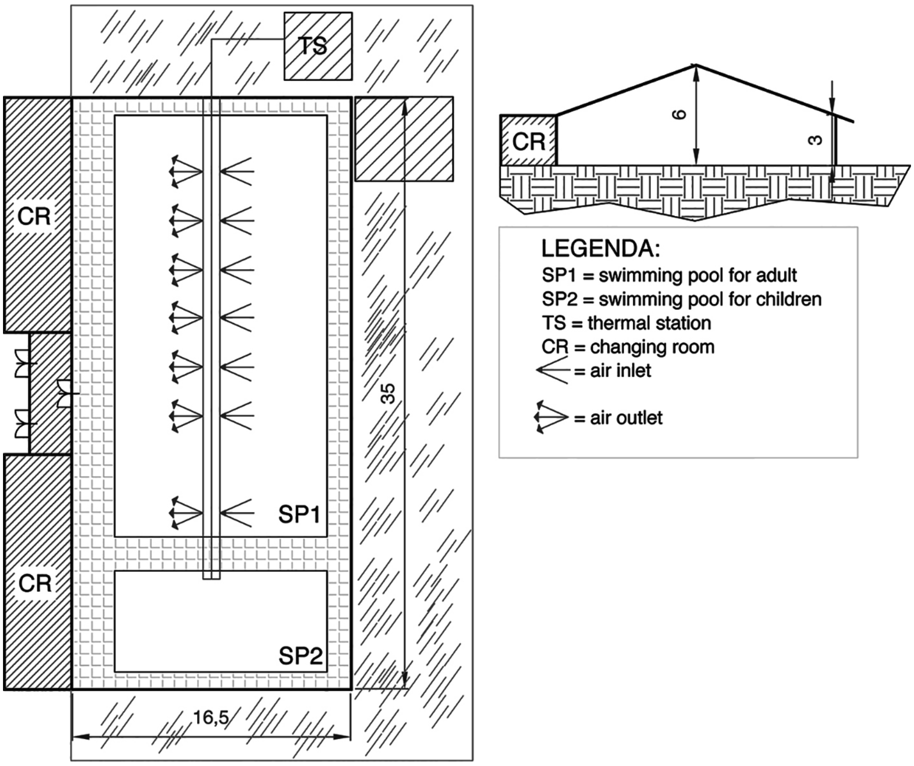


Figure 5.1: Fidia swimming pool layout

Fig. 5.1, the air is supplied from the left side of the central duct, the return circuit is on the right side. In addition, a perimetral system of inlets covers both the long sides of the pool. The structural characteristics together with the air distribution system contribute to create a high horizontal temperature gradient. A preliminary measurement campaign was conducted in this environment to investigate the presence of a non-uniform horizontal air temperature distribution. The measurement system used in the campaign was composed of six wireless sensors measuring air temperature and relative humidity connected to an embedded PC for data logging. The temperature sensors were thermistors with an accuracy of $\pm 0.5°C$ and resolution of $\pm 0.05°C$. The relative humidity sensors were capacitive transducers with an accuracy of ±5% and resolution of ±0.1%. The sensors placement (Fig. 5.2) was designed to reproduce the sensors network approach developed with the sub-zonal model simulation. The sensors were mounted on the perimetral walls at 1.7 meters from the ground, as the position of installation for the existing thermostat. Fig. 5.3 shows the

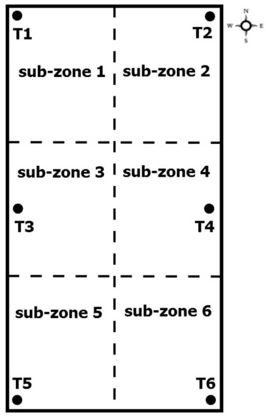


Figure 5.2: Sensor network configuration inside Fidia swimming pool space

air temperature profiles of the sub-zones during a single winter day of January. Following the air temperature trends, it is possible to notice that the HVAC started to work at 08:00 in the morning and temperatures increased until reaching a maximum value after 12:00. This investigation confirmed the presence

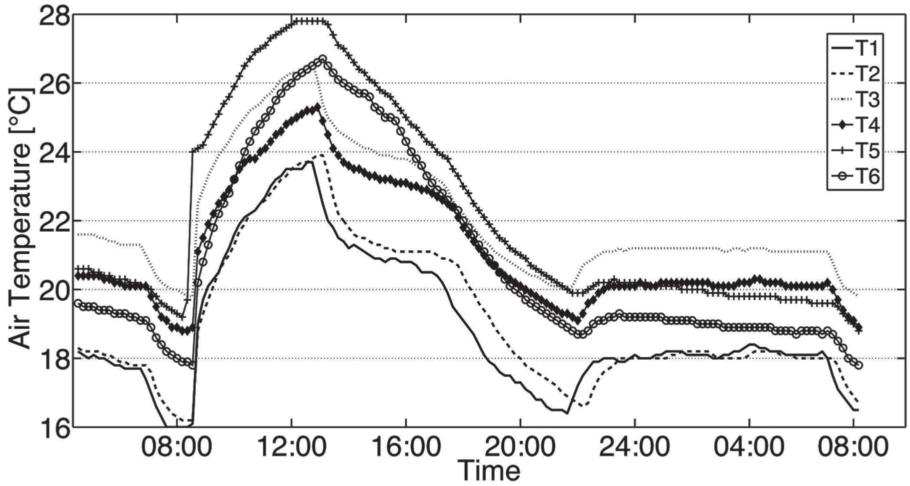
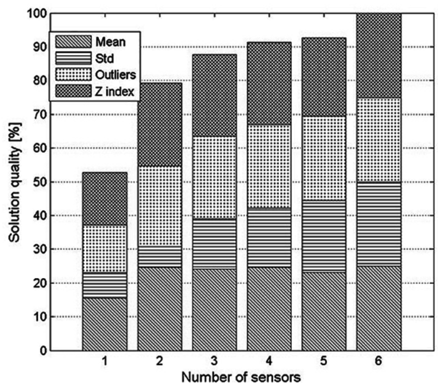


Figure 5.3: Air temperature trends in Fidia indoor swimming pool

of a non-uniform horizontal distribution of the air temperature: a deviation of $4°C$ between the sub-zones 1 and 5 was found during the HVAC working period (Fig. 5.3). Moreover, it can be seen that, when T1 measured a temperature equal to the HVAC set point of $24°C$ fixed by the facility manager, the sub-zones 3, 4, 5 and 6 were exposed to overheating conditions. Therefore, this analysis underlines the necessity to optimize the air temperature measurement inside the environment, so to correct the operational behaviour of the HVAC.

5.1.2 Optimization solution

The purpose of this section is to verify the consistency of the SOU through a comparison between the optimal placement solutions (sensors number and positions) obtained with measured and simulated data. Using the sensor network described in Fig. 5.2, the monitoring campaign was extended for the entire period between the 1st of January to the 31th of January 2013. In practice, the air temperature data collected from field monitoring were submitted to the optimization tool that is implemented in the SOU. The optimization algorithm selected the optimal measurement solutions from 1 to 5 sensors. Fig. 5.4 reports the quality of the solutions expressed in percentage of satisfaction of the Im on the y-axes and the number of sensors used on the x-axis.



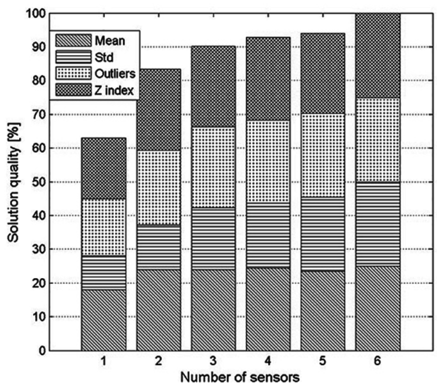


Figure 5.4: Quality indexes of the measurement (left figure) and simulated (right figure) solutions

The zero value on the y-axes is based on the solution that showed the lowest performance, while the 100% is the solution with all the sensors installed (reference condition). The best solution is the one that entails three sensors, which showed a standard deviation lower than the sensor uncertainty compared to the reference condition (six sensors installed).

Table 5.1: Comparison of the statistical features between the measured and simulated optimal solutions

	Simulated data	**Measured data**	**Range**
Mean deviation	$0.02°C$	$0.04°C$	$[0,1]°C$
Standard deviation	$0.3°C$	$0.4°C$	$[0,1]°C$
Outliers	11	11	[0,681]
Z index	0.5%	1%	[0,100]%

In particular, considering that the zero percent of the Std score is equal to $1°C$, the solution with three sensors reduced it to $0.4°C$ (Tab. 5.1). This value is lower than sensor uncertainty ($\pm 0.5°C$), so the solution with three sensors is the optimal one, according to the criterion described subsection 4.2. Concerning the position of installation of the sensors, they should be installed inside the sub-zones signed as number 1, 3 and 6 in Fig. 5.2. Again, looking at the comparison between the optimization results retrieved with simulated and measured datasets in Fig.5.4, a satisfactory correspondence was found. In fact, the simulation replicated the measurement error in terms of statistical indexes and positions of installation (total correspondence between simulated and measured optimal sub-zones). The solution with three sensors is the one that showed a performance index of 90%, the use of an additional sensor would bring just a 2.8% of increase (Fig. 5.4). Therefore, this solution can be considered the optimal one as shown by applying measured data. Tab. 5.1 presents details about the comparison of statistical features between the optimal solutions retrieved with measured and simulated data. The comparison showed the capability of the SOU to reproduce the temperature measurement performance linked with sensors location during the period considered in this study. The optimal sensors placement allowed a decrease of the means and standard deviations from $1°C$ to $0.04°C$ and $0.4°C$ respectively. The number of hours during which the standard deviation is higher than the sensor uncertainty is reduced from 681, given by the worst installation solution, to 11.

5.1.3 Sensor placement and validation

Once that the optimal sub-zones are defined, the next step consists of locating the exact position of installation for each sensor into each sub-zone that composes the optimal solution. Following the procedure described in section 4.4, each sensor is placed along the perimeter. The application of this algorithm to the temperature data coming from measurement and simulation of the Fidia case retrieved the same optimal placement solution for two sensors and slightly different for the third one as shown in Fig. 5.5.

A second phase of validation was performed to compare the temperature mea-

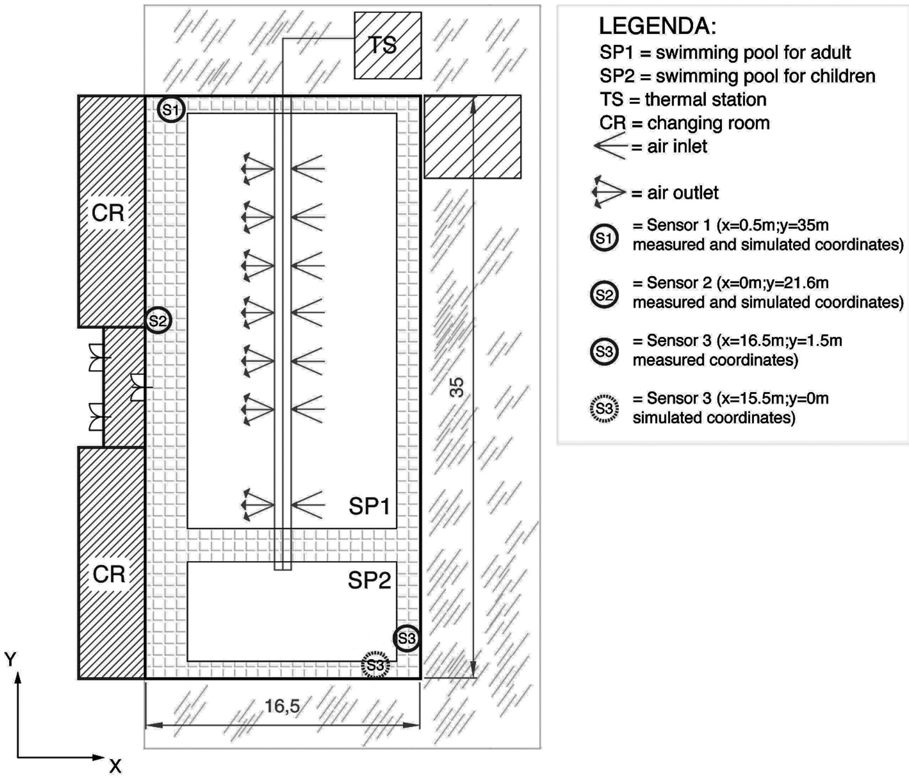


Figure 5.5: Optimal sensors location retrieved with simulated and measured datasets of temperature

sured along the perimeter of the pool area with the one predicted by the SOU. The aim is to verify the consistency of the modelling and interpolation method used to estimate the sensors location in the selected sub-zones. The measurement campaign was performed on April 29th 2013 in order to measure the air temperature at the perimetral walls of the swimming pool with a spatial pace of 2 m and a constant height equal to 1.7 meters. The measurement system was composed of thermocouples type K (calibrated in controlled environment to obtain an accuracy equal to $\pm 0.3°C$), an acquisition module and a PC for data logging. The results shown in Fig. 5.6 demonstrate the capability of predicting the perimetral air temperatures by the SOU modeling component. The simulated trend followed the measured one along the whole perimeter and this is fundamental because the following optimization process relies on the accuracy achievable from the prediction obtained. Basic statistical characteristics re-

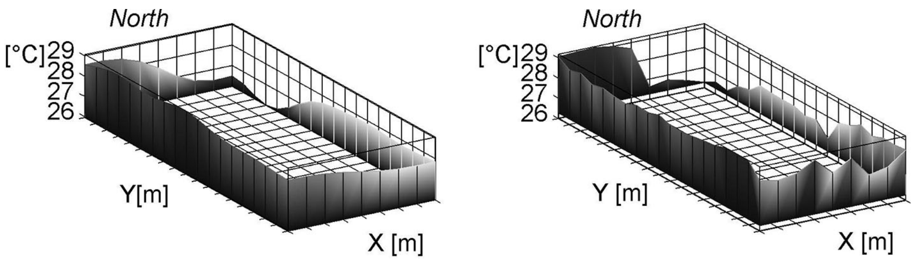


Figure 5.6: Simulated (left side) and Measured (right side) air Temperature trend along the perimeter

garding the simulated and measured air temperature trends along the perimeter are reported in Tab. 5.2. The comparison between min, max, mean values and the total range retrieved from simulated and measured data shows an almost complete matching and confirms the validity of the proposed approach. The

Table 5.2: Comparison of the statistical features between the measured and simulated optimal solutions

	Simulated data	**Measured data**
Min	$26°C$	$25.9°C$
Max	$29°C$	$29.1°C$
Mean	$27.9°C$	$27.9°C$
Range	$3°C$	$3.2°C$

Gradient operator has been applied to the air temperature function (measured and simulated) to understand if and how much the tool is able to follow the air temperature variations along the perimeter of the environment of study. So the following figure represents the difference between the simulated and measured gradients along the x and y directions for the temperature functions, while the value of z has been supposed constant and equal to 1.7 meters, that is the height of installation of the thermocouples, so the value of the Gradient is null along z. Fig. 5.7 shows how the tool is able to follow the fluctuation of the temperature values along the perimeter of the pool, mostly along the two longer sides, while along the small sides, the Fig. 5.7 shows the bigger difference between the two gradients, this discrepancy comes mostly from the presence of large windowed surfaces where the presence of direct solar radiation makes difficult to simulate the temperature fluctuations, anyway those points along the perimeter are not suitable for sensor installation.

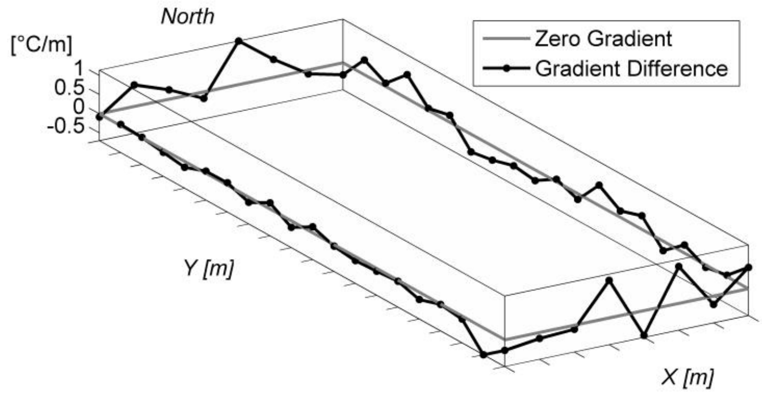


Figure 5.7: Difference between simulated and measured temperature gradients along the perimeter of the swimming pool

5.1.4 Discussion and impact of results

This paragraph investigates how the SOU impacts on the bias of the thermostat measurement, defined as the deviance due to sensor placement and calculated as difference between the measured temperatures and the reference one, comparing measured and simulated data collected during the monitoring campaign performed in the case study. Taken into account the sensors location of Fig. 5.2, the existing thermostat was installed in correspondence of the sensor T1, on the Northern wall. The measurement provided by that location was compared to the mean of all the temperatures measured in the environment. Considering the measured data, a better approximation of the temperature of the environment was calculated with the Eq. 4.1, as the reference condition. The mean temperature was compared with the existing thermostat measurement and with the new optimal sensors placement respectively, than the absolute values of the residuals were plotted as in Fig. 5.8. The comparison showed that the measurement error decreased from a mean value of $0.6°C$ to $0.1°C$ with a

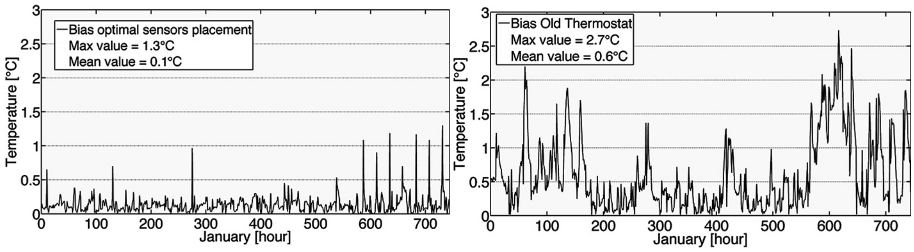


Figure 5.8: Comparison between the old thermostat and the new optimal bias due to sensor placement for temperature monitoring

maximum value that from $2.7°C$ decreased to $1.3°C$. Remarkable is the fact that the number of hour during which the standard deviation is higher than the sensor uncertainty ($0.5°C$) became 11 from the initial 313 of the 744 available, from 42% to 1.5% of the time.

5.2 Case study 2

5.2.1 Description of the environment used as case study

The environment used as case study is a fitness room (Room 1 in Fig. 5.9), which is part of a sport facility sited in Bilbao, Spain. The facility is one of the three pilots where the SportE2 BMS package was installed. The room is placed on the top floor of the three available. It is a medium volume room, it has two neighbour rooms and faces a corridor, it has three windows and the heating system is a single unit fan coil with three inlets as shown in Fig. 5.9. A

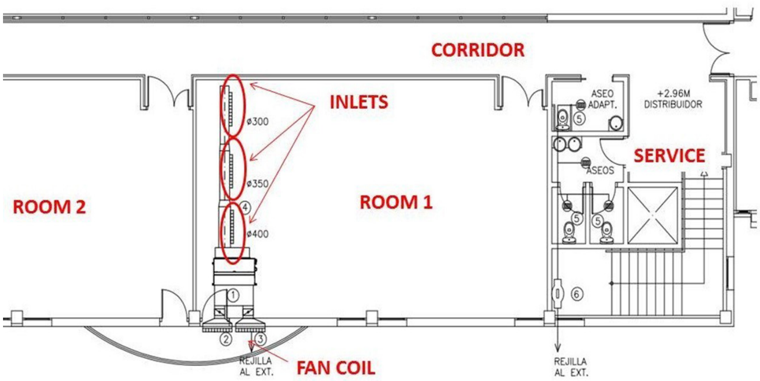


Figure 5.9: Fitness room plant and ventilation system design

measurement campaign was performed for the entire period between the 15th of May and the 15th of June. The measurement equipment was composed by four thermistors (accuracy $\pm 0.5°C$) measuring indoor air temperature in different place of the room and an external sensor monitoring air temperature and relative humidity. The indoor sensor placement (Fig. 5.10) was designed to reproduce the sub-zonal breakdown approach of the simulation model, which divided virtually the fitness room into four sub-zones. The indoor monitoring system was installed on the perimeters walls at 1.7 meters from the ground. The

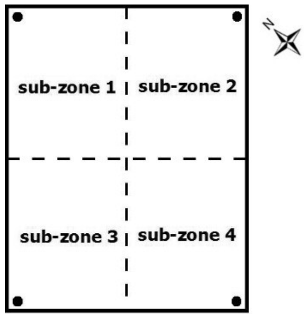


Figure 5.10: Sensor network placement for the fitness room

Fig. 5.11 shows the air temperature profiles inside the sub-zones during a single day. The curves T1, T2, T3 and T4 represent the air temperature distribution

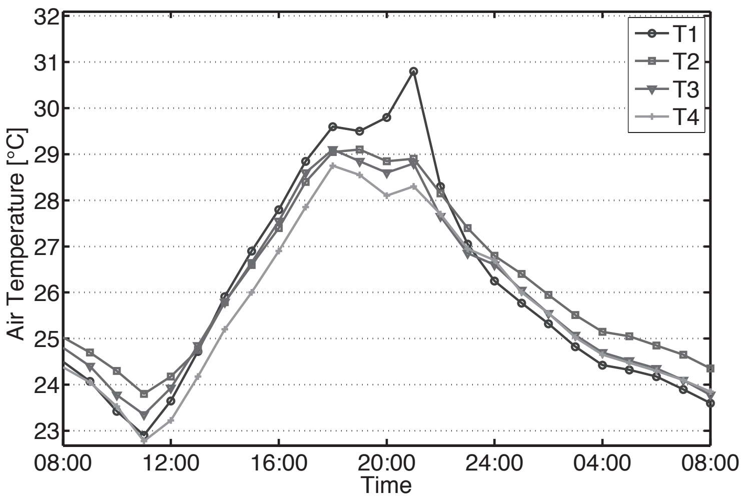


Figure 5.11: Air temperature distribution inside the fitness room

inside the four sub-zones of the fitness room, where a small HVAC performs the climate control of the room. Following the air temperature trends, it is possible to notice that the HVAC started to work after 12:00, then at 22:00 the HVAC stopped and the temperatures started to decrease until morning. This investigation confirmed the presence of a non-uniform horizontal distribution of the air temperature: between the sub-zones 1 and 4 (Fig. 5.11), the deviation reached around $3°C$ during the HVAC working period. Moreover, it can be seen that the sub-zone 1 was exposed to overheating condition, while the sub-zone 4 was not warmed enough. Therefore, this analysis underlines the necessity to optimize the measurement of the air temperature inside the environment.

5.2.2 Model calibration, optimization and discussion of results

The methodology described in this thesis was entirely applied to the fitness room. An initial audit of the facility allows to collect the inputs in order to build an initial sub-zonal model of the test case. The indoor air temperature collected by the monitoring system were filtered, following the method detailed in subsection 3.4.5. The data were divided into 30 daily trends, each trend contains just the data which coincide with the HVAC working schedule. The paths were cross-correlated in order to select the most common indoor thermal behaviour for the environment. The selection process reduced the number of calibration daily trends to 15, which showed a mutual cross-correlation up to 0.9 using the R square coefficient. These 15 paths were used to calibrate the simulation model and for cross-validation process. The simulation model was calibrated using the filtered data. Since that, the virtual volume was divided in four sub-zones; the optimization algorithm provided three (equal to N-1 of the N available sub-zones) different optimal solutions of installation for the monitoring system. The optimal solution with one sensor presented a measurement standard deviation, due to sensor position, equal to the measurement uncertainty of the sensor. Following the criteria for the selection of the best solution defined in 4.2, the optimal placement and number of sensors is the solution with one sensor; the details about statistical features of the measurement deviation due to the sensor position and the point of installation for the sensor are reported in Tab. 5.3 and Fig. 5.12. The optimal model parameters retrieved

Table 5.3: Statistical features of the solution 1 sensor for the fitness room

Mean deviation	$0.8°C$
Standard deviation	$0.5°C$
Outliers	112
Z index	18%

through the calibration process were used to build a single zone model of the environment. The simulation model was used to calculate the hourly PMV values and the energy consumptions due to HVAC operation for the room. Then

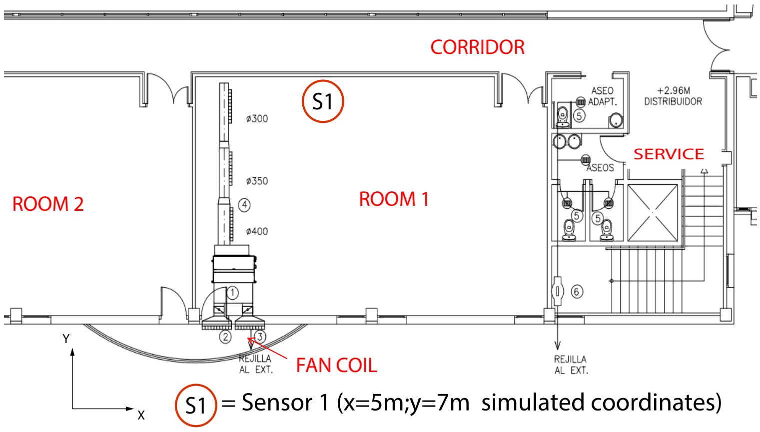


Figure 5.12: Coordinates of installation of optimal sensor position for the fitness room

the uncertainty analysis was carried out using the optimal positioning solutions selected by the optimization algorithm in the previous step. The results are resumed in the next plots. The Fig.5.13 represents the energy consumption deviation in terms of kWh, which would affect the environment in case of using one or more additional sensors to monitor the indoor air temperature inside the environment. The use of an additional sensor, instead of just one will bring a potential decrease of the energy consumption deviation equal to 15 kWh, equal to 0.0035% of the total consumption (4000 kWh), calculated for an entire year of simulation, during the HVAC operational hours. The comparison between the potential savings and the cost of one additional sensor, clearly justified the selection of the solution with only one sensor as optimal for the environment, considering potential energy savings and costs (each sensor node used has a cost of EUR 120). The Fig.5.14 represents the PMV deviation, which would affect the environment in case of using one or more additional sensors to monitor the indoor air temperature inside the environment. The use of an additional sensor, instead of only one would bring a potential decrease of the PMV deviation less than 0.01 during an entire year of simulation, equal to 0.0033% of the entire range of variation of the PMV (± 3). The comparison between the increase of precision on the evaluation of the PMV index and the cost of use of an additional sensor, clearly justified the selection of the solution with just one sensor as optimal for the environment. The cross-validation process was also applied to the calibrated model to evaluate the prediction capability of the model in terms of sensor position. The CV process were applied to the solution with one sensor. This can be justified considering that the solution with one sensor was selected as the one which showed the best performance,

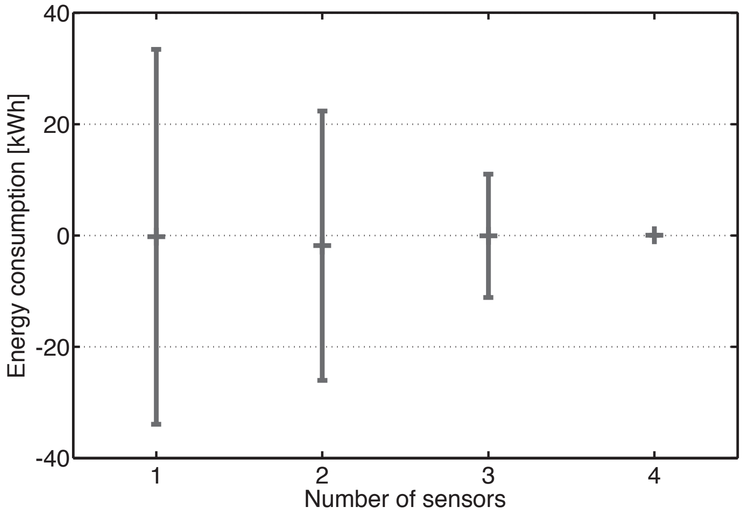


Figure 5.13: Trade-off between energy consumption deviation and number of sensors

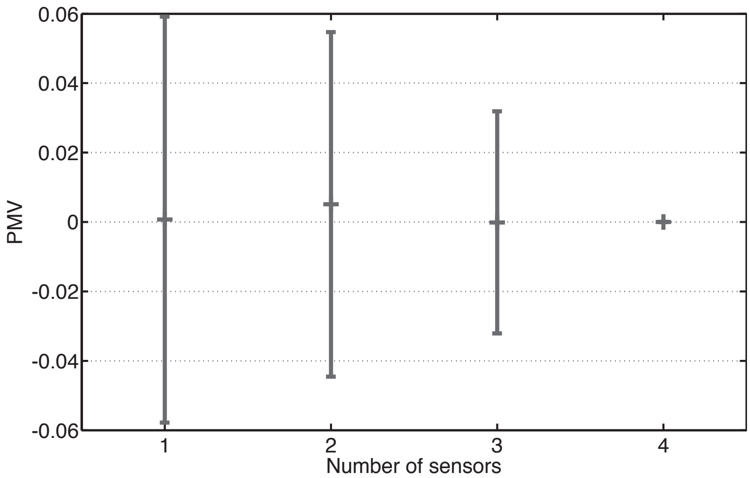


Figure 5.14: Trade-off between PMV deviation and number of sensors

in terms of measurement uncertainty, comfort evaluation end cost constraints. The simulation model was cross-validated for the 15 cases, each time the simulation were calibrated using 14 days and evaluated in terms of sensor position on the remaining day. The comparison between the solutions of sensor positioning from simulation and from real data lead to a final score equal to 92.5% of success on the sensor position. This index can be considered as the quality of prediction of the calibrated simulation model.

5.3 Case study 3

5.3.1 Description of the environment used as case study

This section presents an application of the measurement performance index to measured data retrieved from an high automated building equipped with a BMS and an extensive set of sensors capturing environmental, energy and structural characteristics of the building. The building is a living laboratory sited in Galway, Ireland, where the study presented in this thesis was finalized during a six months research experience performance with the IRUSE research group. The building is called "Engineering Building NUI Galway", it acts as a teaching and learning tool for student and researchers. The test case taken in exam is an open space office sited at the third floor of the building, equipped with a wide range of sensors allowing fine climate control performed by coupled actions between HVAC system and natural ventilation coming from a double glazed facade and automated windowed openings. A BMS operates the monitoring and control of the environmental parameters of the building, the large space, considered in this study, is fully equipped with six thermistors, measuring the air temperature value with accuracy ± 0.3, in six different points, installed on pillars at breathing level, marked with a circle in Fig. 5.15. The temperature data were downloaded for the entire month of January 2015 with a sampling frequency of 7 minutes, a typical day of temperature distributions is reported in Fig. 5.16 , where an horizontal gradient of around $2°C$, can be found between the sensors T5 and T6, during the occupancy hours.

5.3.2 Sensor placement optimization

The objective is to demonstrate the application of the optimization algorithm, based on the measurement performance index to the data gathered from the BMS. The sensor selection process calculated as optimal sensors to be kept, in case of sensors reduction, the sensors T1 and T4 (Fig. 5.15). The statistical features of the calculated solution is reported in Tab. 5.4. The deviance between the reference condition (mean temperature values between the six trends available) and the temperature calculated as mean values between the two sensors selected as optimal ones is reported in Fig. 5.17, the selected time window is a typical day during the week. The optimization process led to the conclusion that to capture the environmental condition of the entire space two sensors of the six available could be used, following the optimal sensors selection criteria developed and presented in 4.2.

Figure 5.15: Sensor network design of open space office, Engineer Building NUI Galway)

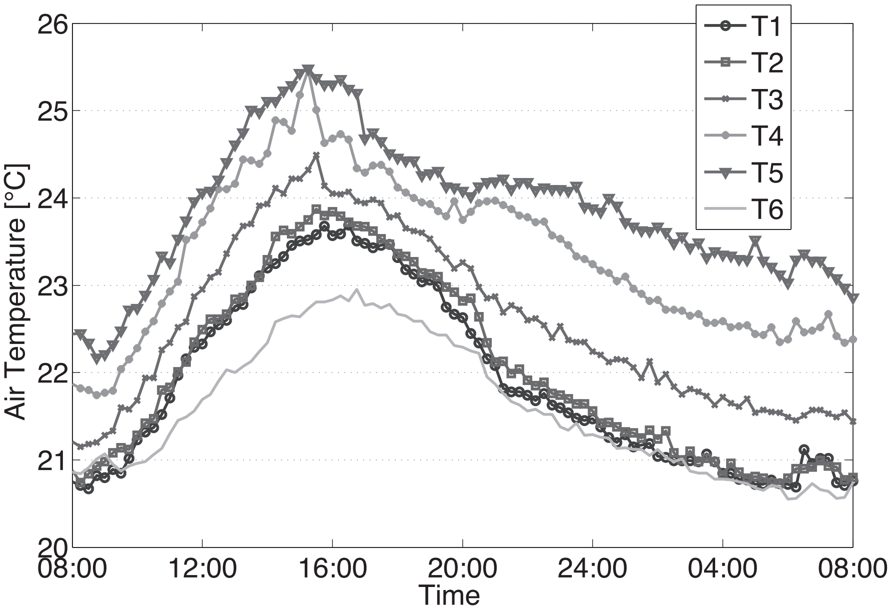


Figure 5.16: Temperature trends inside the open space office during one day, Engineer Building NUI Galway

Table 5.4: Statistical features of the solution 2 sensors for the open space office

Mean deviation	$0.05°C$
Standard deviation	$0.25°C$
Outliers	21
Z index	5%

The main result was that the use of just two sensors for monitoring the temperature inside the space, instead of the initial six (reference temperature), led to measurement performance statistical criteria equal to mean deviation of $0.05°C$, standard deviation equal to $0.25°C$ and 21 of sensors working hours with a standard deviation, due to the sensor location, higher than sensor uncertainty, considering the entire January 2015 as time window for the analysis. So, the use of the two selected sensors for temperature monitoring would bring sufficient measurement accuracy, the use of additional sensors nodes would not provide further useful information.

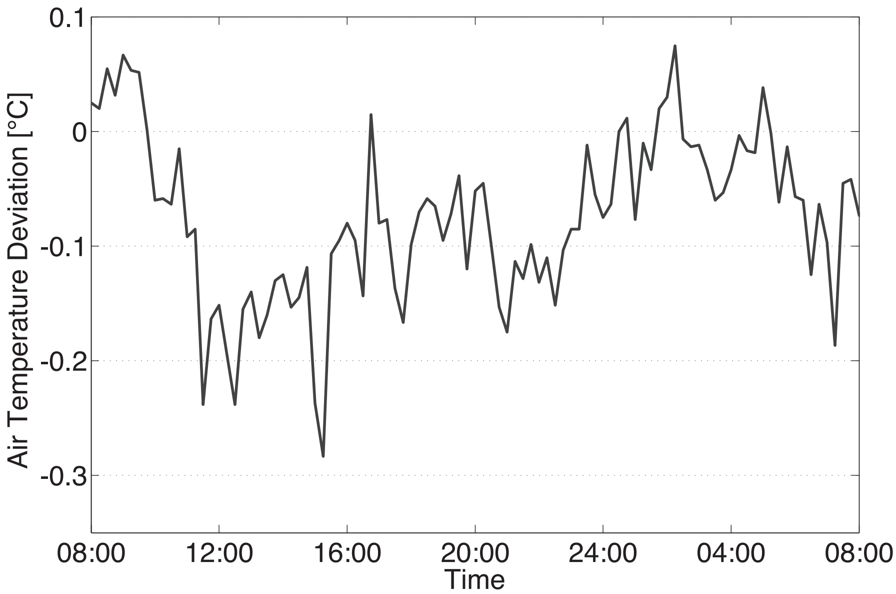


Figure 5.17: Temperature deviance between reference temperature and optimal solution during one day, inside the open space office of the Engineer Building NUI Galway

Chapter 6

Concluding remarks

6.1 Conclusions

This thesis describes a methodology to optimize the air temperature monitoring in large spaces. The theory behind the methodology was explained in the first part of the thesis, where the dataset generation process was described allowing three different approaches based on simulation, calibrated simulation or data driven respectively. Then, it was coupled with an optimization solver, allowing two stages of optimization to calculate the optimal location of the air temperature sensors. The second part of this work was dedicated to the application of the developed method to three different large spaces, starting from an indoor swimming pool, where a maximum deviation of $4°C$ between different zones was found during the HVAC operation. Then, the simulation results were compared with real measurements. The main results are:

- The validation of the tool based on measured data. The best solution of sensors positioning coming from the simulation and measurements corresponds in terms of location and measurement performance.
- The analysis of measured data showed a bias due to the location of the existent thermostat with a mean value of $0.6°C$ and 42% of working hours with a standard deviation, due to the sensor location, higher than sensor uncertainty. The new optimal sensors network decreased the bias to a mean value of $0.1°C$ and only 1.5% of the live time.

The second application was performed in a fitness room, where the complete optimization procedure was applyed, the main results are:

- The application of the sensor placement optimization method based on the measurement performance index retrieved as best solution the one with just one sensor.
- The impact of the measurement uncertainty due to the optimal solution on HVAC consumption was carried out; the use of an additional sensor,

instead of only one would bring a potential decrease of the energy consumption deviation equal to 15 kWh, which represents the 0.0035% of the total consumption (4000 kWh), calculated for an entire year of simulation, during the HVAC operational hours. The comparison between the potential savings and the cost of an additional sensor, clearly justified the selection of the solution with one sensor as optimal for the environment, considering potential energy savings and sensor cost (EUR 120).

- The impact of the measurement uncertainty due to the optimal solution on thermal comfort was carried out; the use of an additional sensor, instead of one would bring a potential decrease of the PMV deviation less than 0.01 during an entire year of simulation, equal to 0.0033% of the entire range of variation of the PMV (±3). The comparison between the increase of accuracy on the evaluation of the PMV index and the cost of use of an additional sensor, clearly justified the selection of the solution with one sensor as optimal for the environment.

- The cross-validation process was also applied to the calibrated sub-zonal model to evaluate the prediction capability, in terms of sensor position. The comparison between the solutions of sensor positioning from simulation and from real data lead to a final score equal to 92.5% of success on the sensor position. This index can be considered as the quality of prediction of the calibrated simulation model.

A third application of the methodology, based just on the measurement performance index, was performed on a high automated building equipped with a widespread set of temperature sensors controlled by a BMS. The optimization process was built on temperature data measured inside an open space office. The main result are that the use of two sensors for monitoring the temperature inside the space, instead of the initial six (reference temperature), leaded to measurement performance statistical criteria equal to mean deviation of $0.05°C$, standard deviation equal to $0.25°C$ and 21 of sensors working hours with a standard deviation, due to the sensor location, higher than sensor uncertainty, considering the entire January 2015 as time window for the analysis. The use of the only two selected sensors for temperature monitoring would bring sufficient measurement accuracy, the use of additional sensors nodes would not provide further useful information.

6.2 Future works

The SOU was developed and applied to sports facilities and an open space office, but other large spaces as entertainment buildings, cruise ship or aeroplane could show same issue related to high gradients of temperature in the occupied area. The SOU will be applied to other building typology allowing a generalization of the proposed solution for the optimal temperature monitoring. The same approach applied to sport facilities should be extended to these type of spaces with the aim to find out how to charaterize the temperature distribution with an effective and practical manner. The initial application presented in this thesis of the tool was useful to validate the overall system but also to provide basis for its replication. The first step forward addressing this aim is already running since the optimization approach proposed in this thesis has been inserted in an European project of the Horizon 2020 framework program, called NewTREND [42]. NewTREND started in September 2015 and it will develop an integrated design methodology for energy retrofit specified for use for individual buildings and at the district level. NewTREND will address all phases of the refurbishment process. To enable the effective application of the methodology, a toolkit will be developed to support each phase from concept design to implementation and operation, fostering collaboration among stakeholders, involving building inhabitants and users and establishing energy performance as a key component of refurbishments. Inside this project, in order to take into account the operational phase of the buildings, the developed Simulation & Design Hub platform (based on IESVE software [43]) will also include a plug-in to a SOU developed by UNIVPM, that, gathered building data and dynamic simulation model results, and will provide the HVAC designer with the optimal sensor location (e.g. re-location of the existing thermostat) which minimizes the measurement error.

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Appendix A

The Sensor Optimization Unit (SOU) is a stand-alone software which runs on desktop or laptop machines equipped with Microsoft Windows 7, 8 and 8.1 (both x86 and x64 versions) and .Net Framework 4.5. If not already present in the machine, the Matlab Runtime Compiler is installed during the installation of the SOU. The computational requirement is low, so it can run on both low and high performing machines and the whole process can be performed in a short time; apart from the time required for the user to input data, the time needed to perform the optimization process is lower than 2 minute for a laptop with medium performances.

This appendix includes the complete user manual of the SOU driving the user through the graphical user interface (GUI). The version of the software described in this section was developed during the $SportE^2$ project, as mentioned in the first part of the thesis. The software contains the last version of the simulation model for the dataset generation, while the optimization solver is based on the previous version dedicated for sport environment. During the last year the optimization core of the software was totally rebuilt, but still not implemented in the software. The thesis author decided to include this user manual, because it will gives a picture of the needed data for run the simulation. The next version of the software will differ just on the data requirement to perform the optimization task.

SENSOR OPTIMIZATION UNIT USER MANUAL

This appendix drives the user through the Graphical User Interface of the Sensor Optimization Unit, in order to get started using it. After the installation, launching the program it opens a window as in **Figure 1**.

Figure 1 – SOU opening window

The upper part of the GUI is a sort of container of the sport facility information, it is organized using a tab menu and the needed information are split under six main categories (General info, Construction, Plant, Internal, Profiles and Positioning); while the lower part of the GUI is a commands menu, it allows the user to do operations as validate the data, save the project, open an existent project and close the program.

The basic idea behind the SOU user interface is that, starting from general information of the sport facility, the user fills each section with needed input data. Two specific buttons (**Figure 1**, elements 10 and 11) are fundamentals to guide the user through the interface to the last tab “Positioning” (**Figure 1**, element 6), where the software completes and displays the calculus of the best positioning solution of sensors installation inside the ambient of study.

Using the tabs (**Figure 1**, elements from 1 to 6), the user can browse along the different sections of the menu, in order to have a visual check of the data inputs: the ones already implemented and the missing data.

The commands bar is illustrated in **Figure 1**; it is composed of five buttons in order to allow the following operations:

- Save current project (**Figure 1**, element 7);
- Open an existent project, already saved into the pc (**Figure 1**, element 8);
- Close the program (**Figure 1**, element 9);

- Data validation: the software checks for each tab, that all the field are filled and the data are suitable (**Figure 1**, elements 10 and 11);

General info

When the user starts the program, the main window opens with the "General info" tab ready to work. The contents of this tab are split in three main categories: site information, wheater data and shape (see **Figure 1**.

Starting from the site information (**Figure 2**(a)) the user should insert the name of the building into the text box "Building name" (**Figure 2**(a), element 1), then pushing the button "Latitude and Longitude Web service calculator", an additional window opens as in **Figure 2**(b).

The user has to insert the country and the city of the sports facility and then press the Google icon; it connects the software to a service powered by Google. This service provides the values of Latitude and Longitude for the location, finally pressing "OK", the values move directly to the related text boxes (**Figure 2**(a), elements 4 and 5).

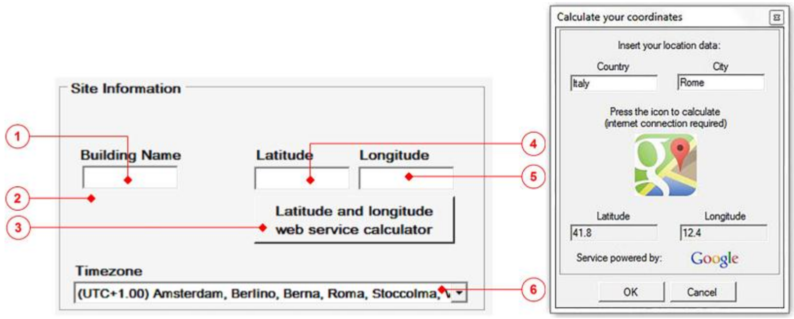

Figure 2 – (a) Site information section – (b) Latitude and Longitude web service calculator

The described web service calculator needs of an internet connection to run; in case the SOU runs offline, the user can always inserts the values of Latitude and Longitude manually inside the two specific text boxes (**Figure 2**(a), elements 4 and 5).

The next step is to define the time zone, the user can easily pick the right one from the list of options available on the list box "Timezone" (**Figure 2**(a), element 6).

After the site information, the user has to deal with wheatear information. The SOU simulates the environment of study, using external input coming from a wheatear file that contains data as: diffuse solar radiation, exterior air temperature, direct solar radiation, cloud cover, outside relative humidity, wind velocity and wind direction; all these data are different depending on the geographical location of the facility.

How to get these data? The user should move the attention to the weather Data section, in **Figure 3**, then should follow the step-by-step description reported below:

1. Pressing a button (**Figure 3**, element 1) the SOU connects directly to web site of the U.S. Department of energy, where weather data for more than 2100 locations in the world are available in EnergyPlus weather format; now inside this web page, the user selects the region of interest and download a zip file that contains three files: IDFEditor document, EPW file and a STAT file; the EPW file is the important one, that needs to be saved;

2. A second button (**Figure 3**, element 2) opens an additional window that requests the directory of the EPW file (available from step 1), once it has been found, just press the command OPEN on the window; if the previous steps were successfully completed, then the two boxes (**Figure 3**, element 6 and 7) will be automatically filled with the EPW file path and EPW file name;
3. After the second step, the button (**Figure 3**, element 3) is enabled, so the user can push it in order to finalize the implementation of the weather data, if the operation succeed, a new window that tells “Meteo file created” appears, then just push “OK” and the meteo process is complete.

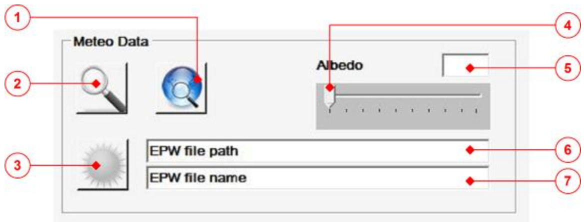

Figure 3 – Meteo data section

After created and loaded the meteo data, the user have to set the Albedo using a track bar (**Figure 3**, element 4), the value will appear on the box named “Albedo” (**Figure 4**, element 5). The Albedo is the fraction of incident radiation that it is reflected by a surface; the concrete, buildings have a lower Albedo than rural areas with trees and vegetation; the most common values of Albedo are shown below:

Natural surface types	Approximated albedo
Blackbody	0
Forest	0.05–0.2
Grassland and cropland	0.1–0.25
Dark-colored soil surfaces	0.1–0.2
Dry sandy soil	0.25–0.45
Dry clay soil	0.15–0.35
Sand	0.2–0.4
Mean albedo of the earth	0.36
Granite	0.3–0.35
Glacial ice	0.3–0.4
Light-colored soil surfaces	0.4–0.5
Dry salt cover	0.5
Fresh, deep snow	0.9
Water	0.1–1
Absolute white surface	1

Figure 4 – Albedo most common values

The last part the site information is dedicated to the shape of the facility, first of all the user have to define the type of the building (Swimming pool, Gym, Multisport Court) through a dedicated list box (**Figure 5**, element 1).

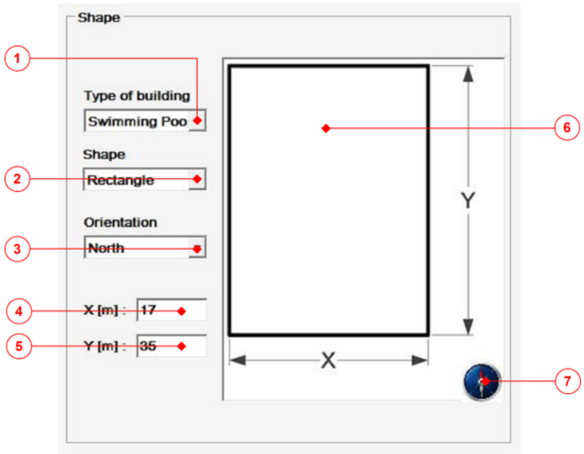

Figure 5 – Shape section

The list box named "Shape" (**Figure 5**, element 2) allows the definition of the shape of the environment and then the shape appears on the dedicated box (**Figure 5**, element 6) as a drawing in plane of the room.

The next step consists on the definition of the Orientation of the environment: the user should imagine himself positioned inside the room, facing one of the two shorts sides of the room (**Figure 5**, element 6, values X), then the user is actually facing the cardinal direction that needs to be selected on the list box signed as "Orientation" (**Figure 5**, element 3).

Finally the values of the geometry of the room expressed in [m], can be defined through the two specific text boxes (**Figure 5**, elements 4 and 5).

After that all the needed information have been inserted in a proper way, the user has to validate the filled data using the specific button (**Figure 1**, element 10): a dedicated algorithm checks the congruence of all the inputs.

For example, if the user inserts as x value a letter, instead that a number, then a message appears, it asks you to correct the value, in order to repeat the data validation process.

In case of successfully submission of the data, a small window that confirms it, will appears, then just press "Ok" and the software brings you directly to the new section "Construction".

Construction

This section allows the definition of the structural characteristics of the facility, as are walls stratigraphy, floor, roof and windows and the window is organized into four main areas:

- Graphical area (**Figure 6**, element 1);
- The tab menu (**Figure 6**, element 2);
- Shadows (**Figure 6**, element 3);
- Windows (**Figure 6**, element 4 and 5);

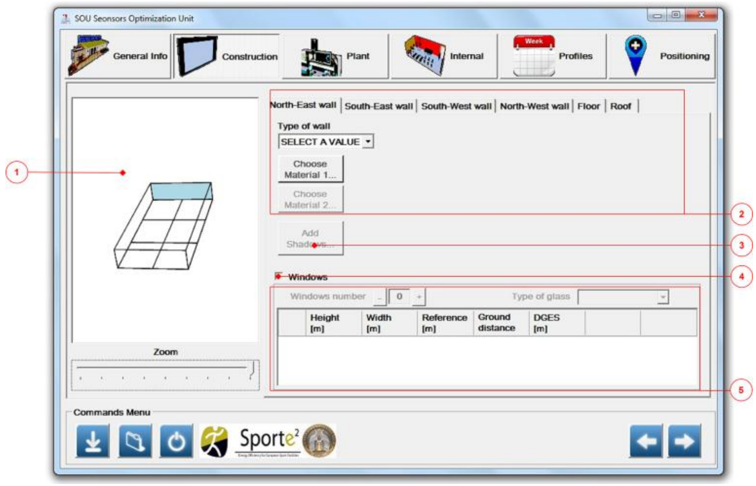

Figure 6 – SOU construction section

1. Select from the tab menu (**Figure 6**, element 2) one wall between the four that compose the perimetral envelope; note that the highlighted surface of the room of the drawing(**Figure 6**, element 1), corresponds with the wall selected from the tab menu;
2. Select from the list box the Type of wall, the available are:
   - External: a wall exposed to the exterior;
   - Internal: a wall entirely shared with an adjacent indoor zone;
   - Mixed: a wall partially external and internal.

Then the next steps depend on the type of wall selected.

External wall

3. Select from the list box named "Type of wall" (element 1 on **Figure 7**), the option "External";

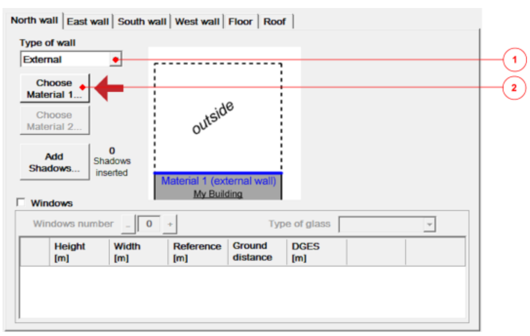

Figure 7 – External wall section

4. In order to define the wall stratigraphy, push the specific button called "Choose Material" (element 2, **Figure 7**), then it opens a window named "Material Layers" (**Figure 8**); this window enables the possibility to create a multilayer stratigraphy (element 7);

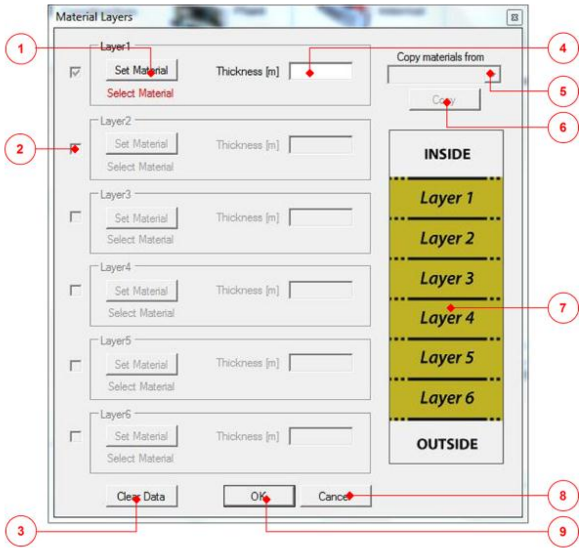

Figure 8 – Material layers window

5. Move to the layer 1 and push the button "Set Material" (element 1, **Figure 8**), it opens the "Material Selection" window (**Figure 9**);

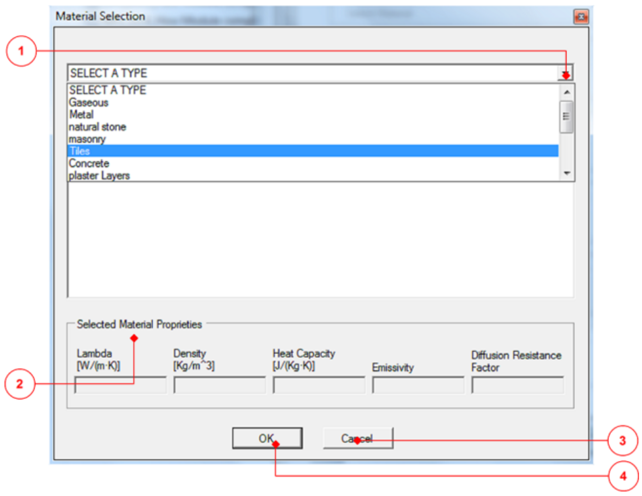

Figure 9 – Material selection window

6. Select the type of the material using the list box "SELECT A TYPE" (element 1 **Figure 9**); the type of materials available are: gaseous, metal, natural stone, masonry, tiles, concrete, plaster layers, other inorganic materials, inorganic insulators, organic insulators, wood materials, bound organic materials except wood and plastic, hard plastic, roof;
7. Once the type has been selected, another list appears into the same box (element 1 **Figure 10**), this list is composed of all the available materials from a specific type;

8. After one material has been selected, the values of its properties (as Lambda, Density, Heat Capacity, Emissivity, Diffusion Resistance Factor) fill the dedicated boxes (element 2, **Figure 10**); if the user is looking for a material that it is not present in the proposed list, it is suggested to take a material that shows similar properties respect the desired one;

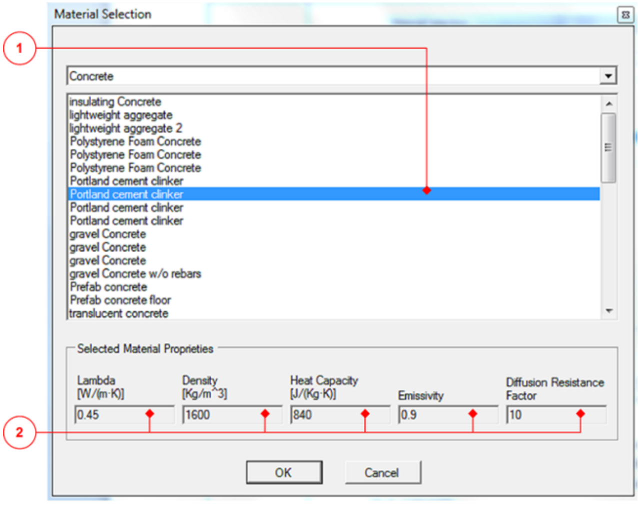

Figure 10 – Material list properties

9. Once the user has found the right material, just press "OK" (element 5), then the material will be inserted into "Layer 1" (element 1, **Figure 8**);
10. Define the thickness [m] of the Layer 1, using the specific text box (element 4, **Figure 8**);
11. If the user want to add a "Layer 2" to the wall, just click the specific check box (**Figure 8**, element 2) then the layer becomes active and properties can be set following the procedure from point 5 to 10; please note that maximum six layers can be added to a wall stratigraphy;
12. When the stratigraphy is complete, just press "OK" (element 9, **Figure 8**) and the stratigraphy will be saved and automatically assigned to the wall, which the user is working on; please note that the working wall is also recognizable through the specific label of orientation (**Figure 6**, Tab menu);

Other notes:

- The stratigraphy of the wall is defined starting from the Layer 1 to Layer 6, from inside to outside (element 7, **Figure 8**);
- During the definition of the wall stratigraphy, the user can use a functionality named "Copy materials from": using the specific list box (element 5 in **Figure 8**), the user can select historical stratigraphy (only from the current project), then using the button "Copy" (element 6, **Figure 8**), the user defines the characteristics of a new wall through an existent one;

13. The button "Clear data" (element 3, **Figure 8**) can be used to clear all the layers present into the window (**Figure 8**) at the same time, in order to start from zero and define a new stratigraphy.

Internal wall

3. Select from the list box (element 1, **Figure 11**), the option "Internal";

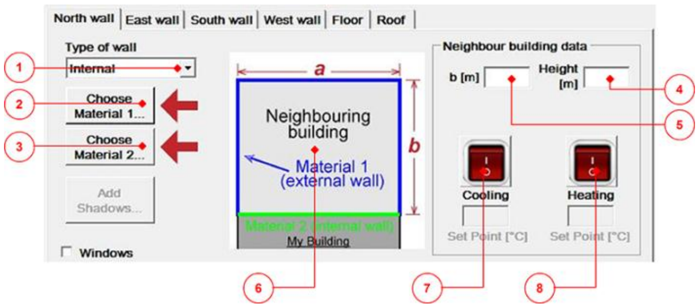

Figure 11 – Internal wall section

4. The button "Choose material 1…" (element 2, **Figure 11**) defines the stratigraphy of the external wall of the neighboring room (element 6,**Figure 11**); then the stratigraphy can be defined following the procedure from point 3 to 12, fully described into the previous section "External wall";
5. The button "Choose material 2…" (element 3, **Figure 11**) defines the stratigraphy of the internal wall, that in this case it is a wall of the zone subject of optimization; the stratigraphy of the wall can be defined following the procedure from point 2 to 8, fully described into the previous section "External wall";
6. To better characterize the neighboring building, the user has also to insert:
   - b [m] = the length of the side of the adjacent building that is orthogonally oriented to the studied environment (**Figure 11**, element 5);
   - Height [m] = the height of the adjacent building (**Figure 11**, element 4);
   - In case of air-conditioned environment, the user should press the specific on/off switch (element 7 and/or 8, in **Figure 11**), in order to enable the two text boxes present under the two switches; in case that the environment has a cooling system, the user can insert the cooling set point [°C], while in case of presence of an heating system, the user can insert the heating set point [°C]; in case of presence of both the solutions, heating and cooling systems, the user can insert both the set points; in case of no heating or cooling system, the user has to leave the two switches off;

Mixed wall

3. Select from the list box (element 1, **Figure 12**), the option "Mixed";
4. The button "Choose material 1…" (element 2,) defines the stratigraphy of the external wall of the neighboring room (element 6,**Figure 12**); the stratigraphy can be defined following the procedure from point 3 to 12, fully described into the previous section "External wall";

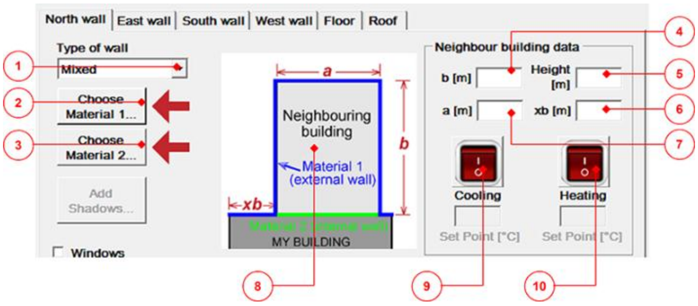

Figure 12 – Mixed wall section

5. The button "Choose material 2…" (element 3, **Figure 12**) defines the stratigraphy of the internal wall that is comprised by the studied zone; the stratigraphy of the wall can be defined following the procedure from point 2 to 8, fully described into the previous section "External wall";
6. The user has also to insert:
   - b [m]= the length of the side of the adjacent building that is orthogonally oriented to the study environment (**Figure 12**, element 4);
   - Height [m]= the height of the adjacent building (**Figure 12**, element 5);
   - a [m]= the length of part of the wall defined as internal one (**Figure 12**, element 7);
   - xb [m] = the length of part of the wall defined as external one (**Figure 12**, element 6);
   - In case of air-conditioned environment the user should press the specific on-off switch (element 7 and/or 8, in **Figure 12**), in order to enable the two text boxes present under the two switches; in case that the environment has a cooling system, the user can insert the cooling set point [°C], while in case of presence of an heating system, the user can insert the heating set point [°C]; in case of presence of both the solutions, heating and cooling systems, the user can insert both the set points; in case of no heating or cooling systems, just live the two switches off;

Once that the stratigraphy of the first wall has been defined in a correct way, the main window appears as in **Figure 13**, then the symbol (element 1, in **Figure 13**) shows up, that means that the stratigraphy has been assigned to the wall, then the button "Add Shadows" (**Figure 13**, element 2) becomes enabled.

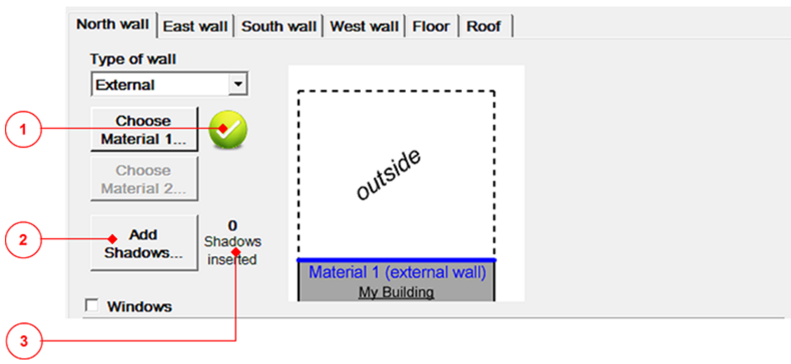

Figure 13 – Screen shot of the construction section window

This button allows the possibility to implement the properties of external shading elements. A step by step description is reported below:

1. Press the button called "Add Shadows…";
2. A new window opens (**Figure 14**);

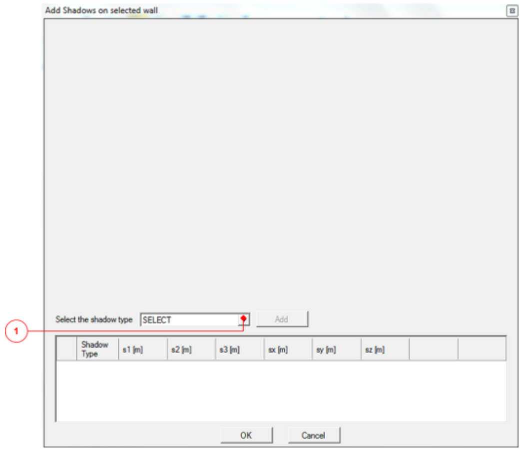

Figure 14 – "Add Shadows" window

3. Select the type of shadow using the list box (**Figure 14**, element 1); there are two options: tree or structures;

Tree

4. If the shadow element is a tree, the window will become as in **Figure 15**;

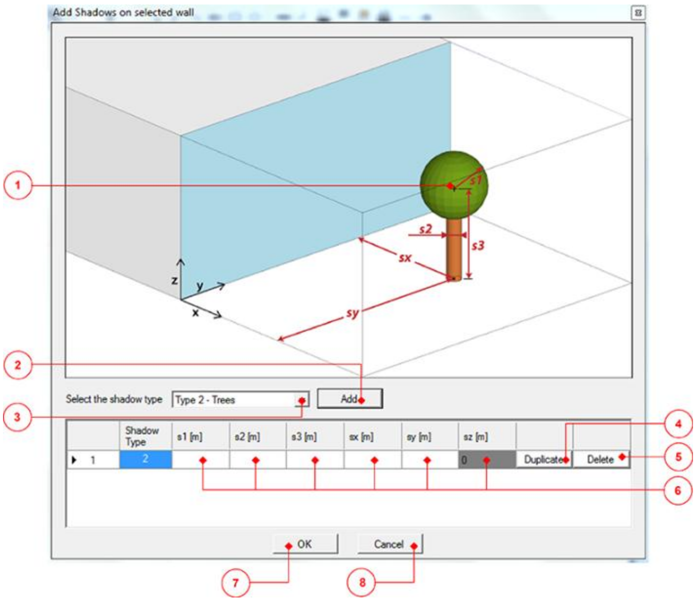

Figure 15 – Type of shadow: Trees

5. Pressing the button "Add" (**Figure 15**, element 2), a new row is added to the table and the row represents the shadow elements, then using the text boxes (**Figure 15**, element 6), the user can insert the following shadow characteristics:

- S1 [m] = value of radius sphere (crown);
- S2 [m] = value of radius cylinder (trunk);
- S3 [m] = height cylinder (height to the center of the crown);
- Sx [m], Sy [m], are the coordinates of the base of the cylinder (trunk) from the left corner of the wall, facing it from outside (as it can be seen in Figure[]);
- Sz [m] is always zero in this case;
- More tree are possible: just push the "Add" button (**Figure 15**, element 2) to get a new tree with new data to fill in;
- Use the "Duplicate" button (**Figure 15**, element 4), if the user want to copy a tree already implemented;
- Use the "Delete" button (**Figure 15**, element 5) to erase a tree already present into the table;

6. Press "OK" (**Figure 15**, element 7) to save and close the window;
7. Press "Cancel" (**Figure 15**, element 8) to close the window without saving the work.

Structures

4. If the shadow element is a structure, the window will become as in **Figure 16**;

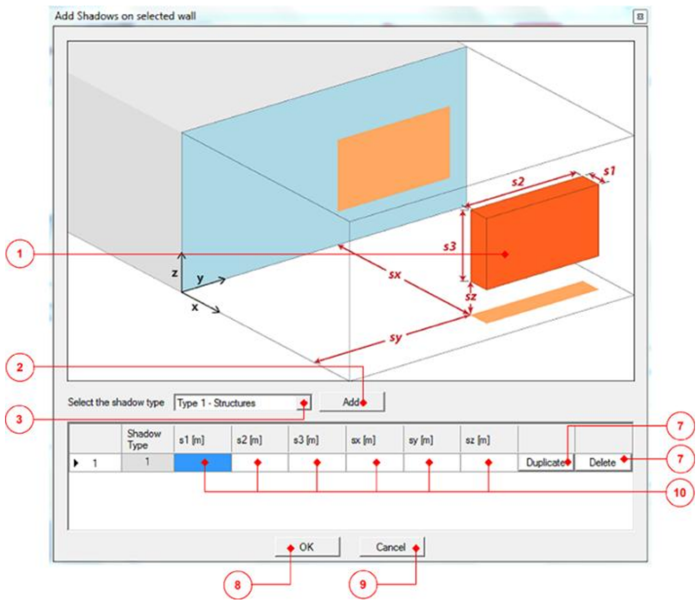

Figure 16 – Type of shadow: Structures

5. Pressing the button "Add" (**Figure 16**, element 2), a new row is added to the table and the row represents the shadow elements, the using the text boxes (**Figure 16**, element 6), the user can insert the following shadow characteristics:

- S1 [m] = size in x-direction (**Figure 16**, element 1);
- S2 [m] = size in y-direction (**Figure 16**, element 1);
- S3 [m] = size in z-direction (**Figure 16**, element 1);
- Sx [m], Sy [m], Sz [m] are the coordinates of the left corner of the structure, from the left corner of the wall, facing it from outside (as it can be seen in **Figure 16**);
- More structures are possible: just push the “Add” button (**Figure 16**, element 2) to get a new structure with new data to fill in;
- Use the “Duplicate” button (**Figure 16**, element 4), if the user want to copy a structure already implemented;
- Use the “Delete” button (**Figure 16**, element 5) to erase a structure already present into the table;

6. Press “OK” (**Figure 16**, element 7) to save and close the window;
7. Press “Cancel” (**Figure 16**, element 8) to close the window without saving the work.

Then the user should check the presence or not of one or more windows for the considered perimetral wall; the procedure to insert the windows is described below:

1. Click on the check box “windows” (**Figure 17**, element 1);

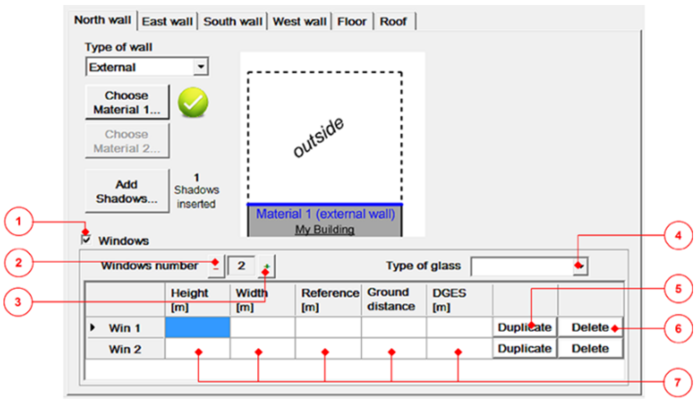

Figure 17 – Windows section

2. Press the button “+” or “-“ (**Figure 17**, element 3 and 2 respectively) to add or delete a window element that in this case is represented by a row of the table in **Figure 17**;
3. Use the list box “Type of glass” (**Figure 17**, element 4) to select the typology of glass available on the list; if the list do not include the requested type of glass, the user has to select the option “custom”, that enables a dedicated text box, where the value of the transmittance of the glass in [W/m^{2}K] should be inserted.
4. Using the text boxes (**Figure 17**, element 7), the user has to insert the following characteristics of the window:

- Height of the window [m];
- Width of the window [m];

- Reference [m]: is the distance of the left corner of the window from the left corner of the wall, facing the wall from outside;
- Distance [m] from the ground of the window ;
- DGES [m]: is the glazing distance from the exterior surface;

5. More windows are possible: just push the “+” button (**Figure 17**, element 3) to get a new empty row in the table, ready to be filled with new data;
6. Use the “Duplicate” button (**Figure 17**, element 5), if the user want to copy a window already implemented;
7. Use the “Delete” button (**Figure 17**, element 5) to erase a window already present into the table;

The described procedure applied for the selected wall has to be extended to the remaining perimetral walls that compose the environment: just select from the tab menu the next wall and repeat this procedure.

Then the next step consists on the definition of the characteristics of the floor.

Floor

The user has to establish if the study environment is at a low ground or not; then selecting the tab “Floor” from the tab menu (**Figure 18**, element 1), the main window appears as in **Figure 18**.

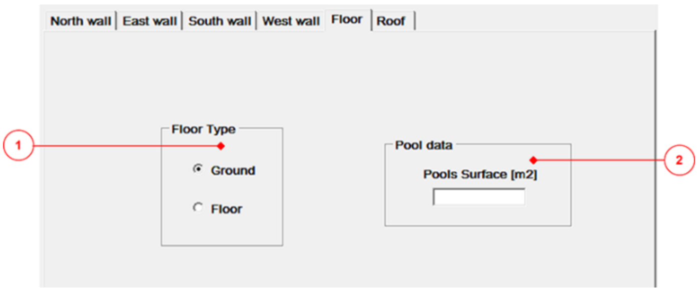

Figure 18 – Floor section

In case that the environment is situated at a low ground, the user has to select the “Ground” radio button inside the “Floor Type” panel (**Figure 18**, element 1); in case of the room of study is situated on an upper floor level than the ground level, the user has to select the “Floor” radio button inside the “Floor Type” panel (**Figure 18**, element 1); in case of the environment of study is an indoor swimming pool, the user has to insert the value in [m^2] of the pool surface into the text box “Pool surface” inside the panel “Pool data” (**Figure 18**, element 2).

Roof

Once defined the floor properties, the user has to define the characteristics of the roof; then selecting the tab “Roof” from the tab menu (**Figure 19**, element 1), the main window appears as in **Figure 19**.

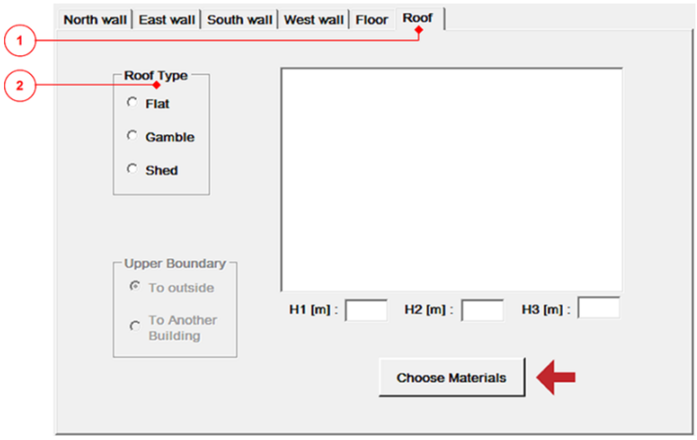

Figure 19 – Roof section

The user has to select the type of the roof of the environment of study between the available ones; the options are situated into the "Roof type" panel (**Figure 19**, element 2); depending on the type of the roof, the user has to insert different data; let us separate the approach based on the type of roof.

Flat roof

If the roof of the environment of study is a flat one, the user has to select the "Flat" radio button inside the "Roof Type" panel (**Figure 20**, element 1); the relative drawing of the roof appears inside the dedicated box(**Figure 20**, element 3).

Then the user has to define: if the roof is actually a roof, so it is exposed to the exterior, or it is a ceiling that divides the room from the upper floor; in case of first option, the user has to select "To outside" from the "Upper Boundary" panel (**Figure 20**, element 2); in case of second option, the user has to select the "To another Building" inside the "Upper Boundary" panel (**Figure 20**, element 2).

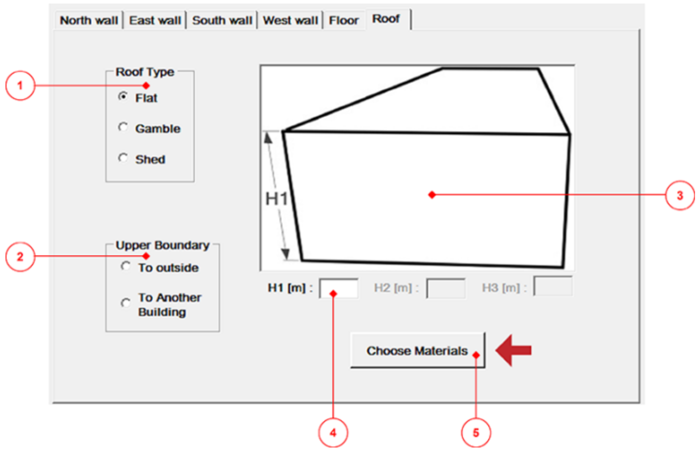

Figure 20 – Roof section after the flat roof selection

After that, using the text box "H1" (**Figure 20**, element 4), the user can insert the eight of the environment of study; then the button "Choose Materials"(**Figure 20**, element 5) allows the definition of the roof stratigraphy through the same procedure previously described for the external wall; note that in case the roof is a ceiling between two floors, the user can skip the definition of the stratigraphy of it.

Gamble roof

In case the type of the roof is gamble, the procedure to inserts the inputs is similar to the described on the flat section and differ only because: first the “Upper Boundary” panel (**Figure 20**, element 2) is disabled, second the user has also add the values ”H2”, ”H3” as features of the roof.

Shed roof

The last available option for the type of roof is Shed; the procedure to inserts the inputs is the same of the one adopted for the Gamble roof, the only difference is that the user has to insert only the values of “H1” and “H3” without the “H2” value.

After the implementation of the features of the Roof, the user has complete the definition of the characteristics of the environment envelope. The next button in the command line validates the data, if the inputs are correct, the SOU will open a window to notify it and then it will move to the next section “Plant”.

Plant

This section is totally dedicated to the heating and cooling plant of the environment; the main window is organized as in **Figure 21**, the space is split into six main groups: heating, cooling, humidification, dehumidification, distribution (**Figure 21**, elements from 1 to 6).

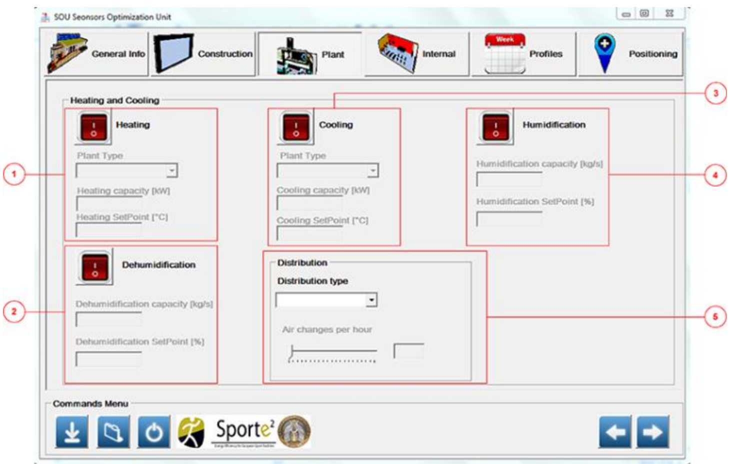

Figure 21 – SOU plant section

First of all the user should check the features of the plant, including typology (heating/ cooling), capacity and distribution type; the user has also to check the capabilities of the heating/conditioning control system that serves the environment. The following part of this paragraph is dedicated to the data implementation.

Heating

1. Press the button “Heating” (**Figure 22**, element 1), in order to enable the possibility to insert the heating features;

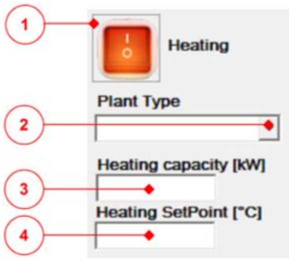

Figure 22 – Heating section of the Tab “Plant”

2. Select from the list box “Plant Type” (**Figure 22**, element 2) the available typologies of the heating plant for the environment:
    - Gas boiler;
    - Biomass boiler;
    - CHP (Combined Heat and Power plant);
    - Mixed (Gas boiler and Biomass boiler, Gas boiler and sun panels and so on);
3. Heating capacity [kW] (**Figure 22**, element 3): the maximum heating capacity that the heating system can provide to the zone considered; the user can find this value on the datasheet of the machine, in case the heating system serves only the ambient of study. If the same machine is providing heating for more zones, the user should estimate the heating capacity that is dedicated only to the zone considered; if it is unknown, the value ‘-2’ can be used, then the SOU will estimate a reasonable value of the maximum heating capacity; the use of this last methodology should be avoid, because it is very rough and should be adopted only in case of absolute impossibility to get the information;
4. Heating SetPoint [°C] (**Figure 22**, element 4): is the desired air temperature value that the control system will aim to reach inside the environment.

Cooling

1. Press the button “Cooling” (**Figure 23**, element 1), in order to enable the possibility to insert the cooling features;

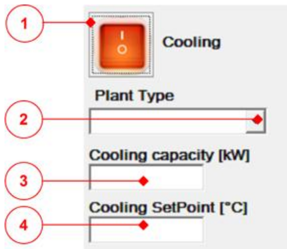

Figure 23 – Cooling section of the Tab “Plant”

2. Select from the list box “Plant Type” (**Figure 23**, element 2) the available typologies of the heating plant for the environment:
    - Chiller;
    - Heat pump;

- Split;

5. Cooling capacity [kW] (**Figure 23**, element 3): the maximum cooling capacity that the cooling system can provide to the zone considered; the user can find this value on the datasheet of the machine, in case the cooling system serves only the zone considered. If the same machine is providing cooling for more zones, the user should estimate the cooling capacity that is dedicated only to the zone considered. If it is unknown, the value '-2' can be used, then the SOU will estimate a reasonable value of the maximum cooling capacity; the use of this last methodology should be avoid, because it is very rough and should be adopted only in case of absolute impossibility to get the information;
3. Cooling SetPoint [°C] (**Figure 23**, element 4): is the desired the air temperature value that the control system will aim to reach inside the environment.

Humidification

1. Press the button "Humidification" (**Figure 24**, element 1), in order to enable the possibility to insert the humidification capabilities of the plant; please make sure that the plant has this capability of control on the air humidification of the ambient of study;

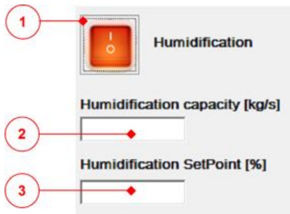

Figure 24 – Humidification section of the Tab "Plant"

2. Humidification capacity [kg/s] (**Figure 24**, element 2): the maximum humidification capacity that the plant can provide to the zone considered; the user can find this value on the datasheet of the machine, in case of the plant is specifically dedicated to the ambient of study. If the same machine is providing humidification for more zones, the user should estimate the humidification capacity that is dedicated only to the zone considered. If it is unknown, it is strongly recommended to live this feature disable;
3. Humidification SetPoint [%] (**Figure 24**, element 3): is the desired the percentage of air humidity that the control system will aim to reach inside the environment.

Dehumidification

1. Press the button "Dehumidification" (**Figure 25**, element 1), in order to enable the possibility to insert the dehumidification capabilities of the plant; please make sure that the plant has this capability of control on the air dehumidification of the ambient of study;

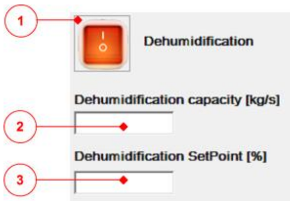

Figure 25 – Dehumidification section of the Tab "Plant"

2. Dehumidification capacity [kg/s] (**Figure 25**, element 2): the maximum dehumidification capacity that the plant can provide to the zone considered; the user can find this value on the datasheet of the machine, in case of the plant is specifically dedicated to the ambient of study. If the same machine is providing dehumidification for more zones, the user should estimate the dehumidification capacity that is dedicated only to the zone considered. If it is unknown, it is strongly recommended to live this feature disable;
3. DeHumidification SetPoint [%] (**Figure 25**, element 3): is the desired the percentage of air humidity that the control system will aim to reach inside the environment.

Distribution

The distribution consists on the way that the plant adopt to provide heated or cooled air inside the ambient of study; then using the specific list box (**Figure 26**, element), the user is able to select the distribution system between: HVAC (Heating, Ventilation and Air Conditioning), Radiators, Floor heating/cooling system, mixed (a mix between the previous ones).

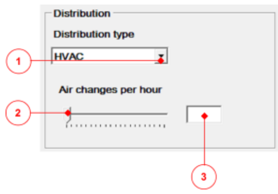

Figure 26 – Distribution section of the Tab "Plant"

Then the user can set the value of Air changes per hour (number of volumes of the environment per hour) through a specific track bar (**Figure 26**, element 2) that write the value inside the dedicated text box (**Figure 26**, element 3). If this value is unknown, the user should have a look of local building codes that stipulate the amount of ventilation required for Sports environments.

When all the data have been implemented, just move to the command line and validate the inputs, pushing the specific button (**Figure 1**, element 10) , if the inputs are correct, the SOU will open a window to notify it and move to the next section "Internal".

Internal

This section is dedicated to the internal thermal loads (e.g. occupants doing sport, spectators, equipment). The window is organized as in **Figure 27**, the space is split into two main spaces: a 3D view of the room and a table to input loads properties.

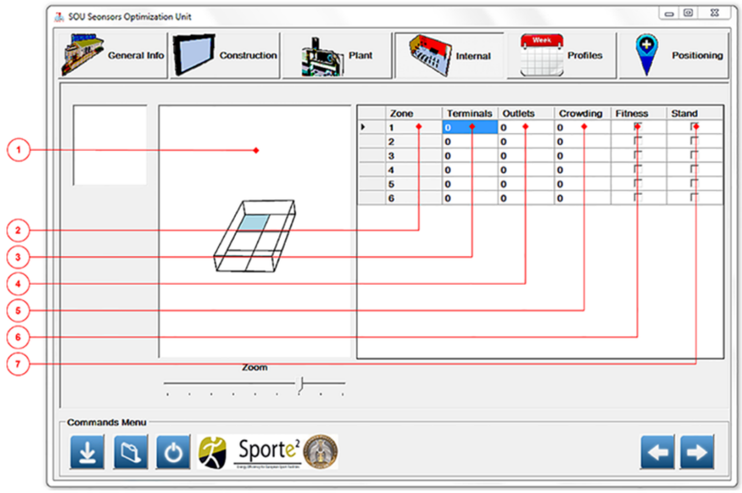

Figure 27 – Tab "Internal" of the SOU interface

The environment is split into N sub-zones (**Figure 27**, element 1) and the table has a number of rows equal to the number of the sub-zones; each row of the table, will define the features of the internal load inside that specific sub-zone.

The drawing has been done, keeping the orientation of the two dimensional drawing presented in **Figure 27**.

The table has six columns, each of them is described below:

- Zone (**Figure 27**, element 2) represents the current zone where the user is defining the specific internal load;
- Terminals (**Figure 27**, element 3) is the number of supply air inlets that is present inside a specific zone;
- Outlets (**Figure 27**, element 4) is the number of return air outlets that is present inside a specific zone;
- Crowding (**Figure 27**, element 5) is the percentage of people usually occupying the sub-zone; the sum of all the crowding values must be 100%. As an example, a gym where the space is divided in: one part where usually there are just machine and the rest of the gym is dedicated to fitness course; then inside this part of the gym usually are present more people than into the first one; so the user should try to express the crowding of each zone in percentage;
- Fitness (**Figure 27**, element 6): check this check box if there is sport activity in that zone;
- Stand (**Figure 27**, element 7): check this check box in case of terraces with spectators.

When all the data have been implemented by the user, just move to the command line and validate the inputs, pushing the specific button (**Figure 27**, element 10); if the inputs are correct, the SOU will open a new window to notify it, then automatically it moves to the next section "Profiles".

Profiles

This section is dedicated to the definition of the profile of use. The main window (**Figure 28**) is divided into two main parts called "Profile information" (**Figure 28**, element 1) and "Weekly assignment" (**Figure 28**, element 2).

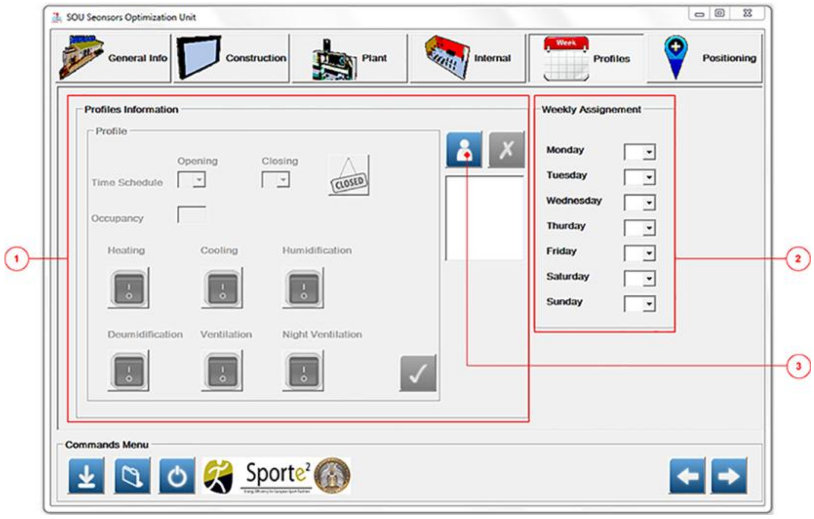

Figure 28 Tab "Profile" of the SOU interface

The user needs to insert the inputs from the panel "Profile information" and, as shown in **Figure 28**, the panel is disable at this stage; then the next steps are following reported:

1. Push the button (**Figure 28**, element 3), it enables the panel (**Figure 29**), after that the SOU is ready to create the first profile of use;

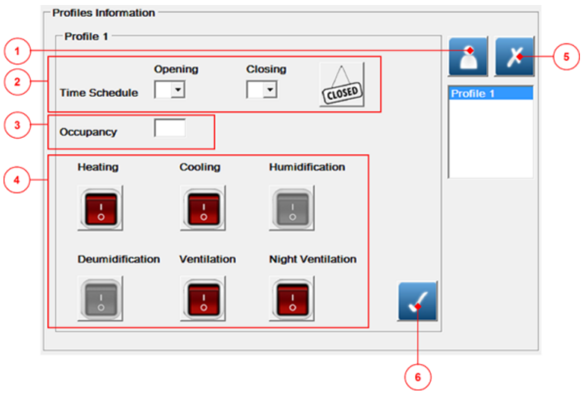

Figure 29 "Profile" panel of the "Profile" Tab of the SOU interface

2. Define the "Time Schedule" using the two list boxes (**Figure 29**, element 2): using the "Opening" and "Closing" list boxes, the user can define the opening and closing hours. Each profile covers one day period; the user cannot create two profile to use on the same day. If the user wants to create a day closed, just press the button "Close" (**Figure 29**, element 2);
3. Define a rough estimation of the possible occupancy value (number of people) for a specific profile of use;
4. Using the switches in **Figure 29** element 4, the user can define the plant usage related to that profile; note as in **Figure 29** not all the switches are enabled, this because they are enabled or not based on the settings made inside the "Plant" section.

5. Then press the button in **Figure 29**, element 6, in order to save the Profile; this operation is fundamental in order to assign the profile during the next steps;
6. Following the previous steps, the user can create maximum 7 profiles, one per each day of the week; use the button in **Figure 29**, element 5, in case the user needs to delete a Profile previously made;

Then the user should move to the other part of the window: "Weekly assignment" reported in **Figure 30**.

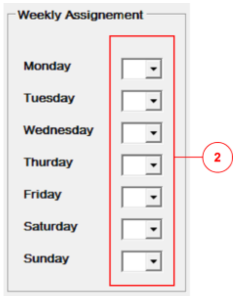

Figure 30 – "Weekly Assignment" panel of the Tab "Profile" of the SOU interface

The user has just to use the list boxes (**Figure 30**, element 2) and for each day of the week choose the specific profile of use for the environment.

When the user has completed the implementation of all the inputs, just press the validation button (**Figure 30**, element), then if all the data implementation process has been done in a proper way, the message "Data validation complete" appears; it means that SOU is ready to calculate the solution.

Positioning

The tab "Positioning" represents the final step that brings the user to the solution for the sensors positioning. The main window is organized into two main areas: a graphical box (**Figure 31**, element 1) and panels for data inputs (**Figure 31**, element 2).

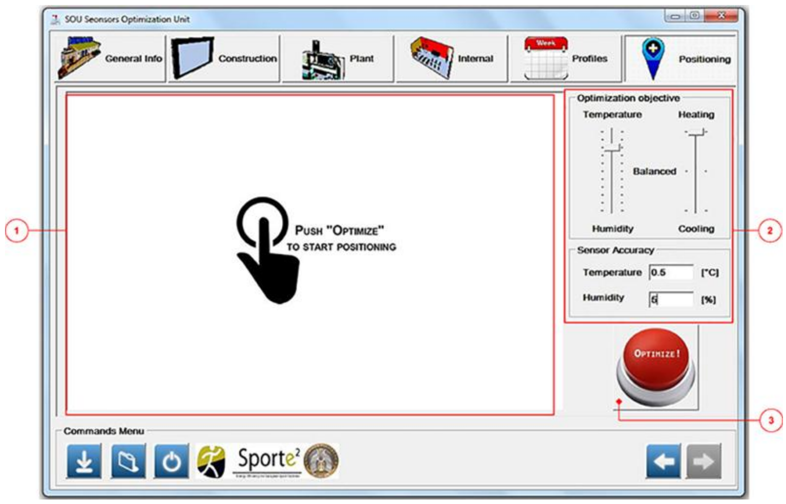

Figure 31 – Tab "Positioning" of the SOU interface

Before starting the calculus of the optimal solution, the user has to insert additional parameters using the panel "optimization objective" (**Figure 31**, element 2), where there are two track bars:

1. The track bar on the left side of the panel is related to the weighting factors that influence the optimization process. The track bar (**Figure 32**, element 1) allows 10 different positions. In the case that a greater accuracy of the air temperature measurement is required, the bar should be moved toward the "Temperature" side. The optimization process is thus configured to reach the maximum accuracy of the temperature measure. In the case that a greater accuracy of the relative humidity measurement is required, the bar should be moved toward the "Humidity" side. In the case of a balanced optimization between Temperature and Relative Humidity, the slider of the bar should be leaved in the position "Balanced": the optimization weights are equally divided by 50% in each side. The selection of these weights defines the balance point to be used by the optimization procedure. For this reason, the selection should be performed paying attention to the end-use of the measuring system (e.g. simple comfort evaluation, feedback to HVAC control system etc.).

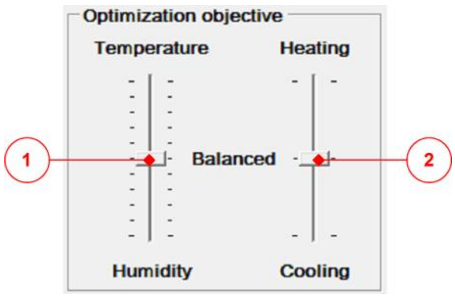

Figure 32 – Optimization objective options of the SOU

2. The track bar on the right side is related to the type of plant and the profile of use of the environment; the slider (**Figure 32**, element 2) has three positioning options:
   - Heating: if only heating is provided, the optimization considers only the heating period of the year;
   - Cooling: if only cooling is provided, the optimization considers only the cooling period of the year;
   - Balanced: if heating and cooling are provided, the optimization considers the period of the entire year; if the comfort monitoring for the entire year is required, the air T/RH values are fundamentals parameters for the calculus of comfort indicator as PMV value.

Based on the type of the sensors utilized inside the environment, the user has to fill the two text boxes "Temperature" and "Humidity" inside the panel "Sensor accuracy" (**Figure 31**, element 2). The first text box should be filled with the value of the accuracy of the temperature sensor expressed in [°C], the second text box should be filled using the value of the accuracy of the relative humidity expressed in [%]. The sensor data sheet usually provides the accuracies.

Let us make an example to better clarify the definition of the optimization parameters. The environment of study is a gym and it has only a heating system. The control system is based just on the temperature value and it works just using the temperature value coming from the thermostat that measures also the relative humidity inside the environment. The owner of the facility wants to know also the comfort level that there is inside the room during the entire year. Therefore, the optimization parameters should be set as: the track bar on the left side of the panel has to be positioned on Temperature side, the other track bar has to be set in balanced position.

After the definition of all the optimization parameters, the SOU is ready to run the optimization process, then the user should just press the red button (**Figure 31**, element 3) and wait until the solution will appears on the dedicated graphic box (**Figure 31**, element 1).

The SOU produces as output a 3D draw (Figure 33) of the optimal solution for the sensors positioning inside the environment.

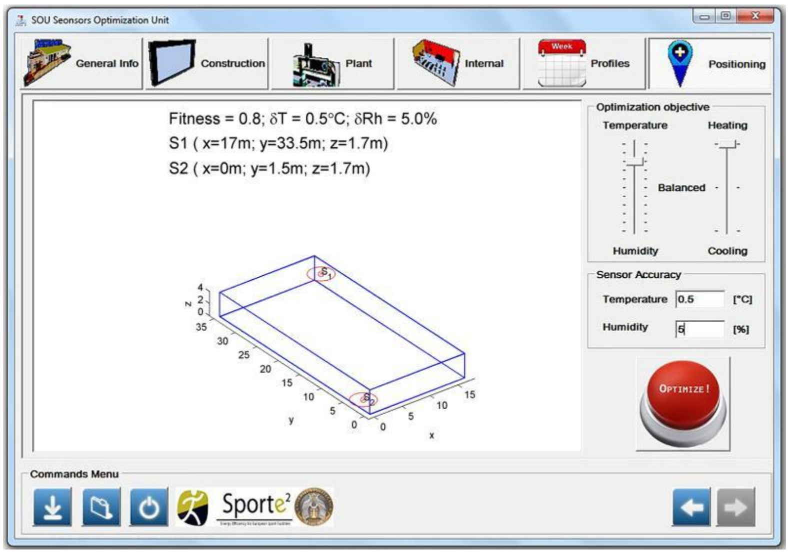

Figure 33 – Output window of the SOU

The SOU output (**Figure 33**) contains:

- δT e δRH that represent the values of measurement uncertainties obtained with the solution provided. These values include both the uncertainties due to the sensors and to the location;
- the coordinates of installation for the sensor/sensors, expressed in [m] using a Cartesian reference system, included into the solution drawing. The orientation of the drawing follows the one defined on the two dimensional scheme reported in **Figure 5**.

The sensor/sensors should be located at 1.7 [m] from the floor, considered as typical thermostat height, near the occupied zone.