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A tool for the optimal sensor placement to optimize temperature monitoring in large sports spaces

M. Arnesano *, G.M. Revel, F. Seri

Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Via Brecce Bianche, Ancona 60131, Italy

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ABSTRACT

The Sensor Optimization Unit (SOU) is a tool, meant to be used by HVAC engineer, for the optimization of temperature sensors placement in large sports spaces, where the HVAC system usually maintains climate conditions actuating control rules based on one temperature sensor, installed in the return air duct or in a single point of the space, without taking into account the indoor air temperature distribution. The SOU characterizes the indoor horizontal air temperature distribution which can be retrieved with a simulation model or field measurement. A dedicated measurement performance index is calculated to determine the optimal sensors location that provides the maximum accuracy with the minimum number of sensors to be deployed. The application and validation of the tool in a real indoor swimming pool outlined that the measurement uncertainty due to the incorrect location of the existing thermostat was higher than ± 0.5 °C (thermostat uncertainty datasheet) for the 42% of the period considered. The optimized placement determined with the SOU decreased that period to 1.5% of the overall time.

1. Introduction

One of the main challenges concerning the environmental monitoring of sports areas is the accurate measurement of the indoor thermal conditions. In fact, sports facilities encompass large spaces, such as swimming pools or indoor courts, where the air temperature is not homogeneous and a significant horizontal gradient may be present together with the typical vertical stratification. This non-homogeneity is generally due to large dimensions, building characteristics, incoming solar radiation, ventilation system and heating/cooling sources. The consequence is that the traditional measurement of indoor air temperature could achieve a level of uncertainty that hinders an accurate comfort evaluation and control. In fact, a single temperature sensor is commonly used to retrieve the indoor conditions, usually installed in the return air duct or in a single point of the environment, without taking into account the air temperature distribution in the occupied zone. The description of the criteria adopted to design the monitoring system concerning number of sensors and location is often omitted, since it is generally based on experience and without the use of supporting tools that capture the real thermal characteristics of the environments. Thus, a dedicated methodology allowing the optimization of sensor network focused measurement accuracy, minimal number and location of sensors is needed.

The work presented in this paper is part of the FP7 EU project SportE2 [1] that developed a scalable and modular BMS (Building Management System) dedicated to sports and recreational buildings. The European Sport and Recreation Building Stock accounts for approximately 1.5 million buildings or 8% of the overall building stock. These facilities are unique by their physical nature, their energy consumption profiles, the usage patterns of people inside, ownership, and comfort requirements, so a dedicated BMS is needed. The SportE2 BMS is composed of four modules to provide smart metering, integrated control, optimal decision-making and multi-facility management. The smart metering system is responsible of the whole building monitoring to capture energy performance [2] and characterize the building services operation (HVAC, boilers, comfort etc.) [3]. In particular, the tool presented in this paper was developed and applied to optimize the design of part of the overall smart metering system to obtain a refined measurement of the indoor air temperature in large spaces. The data acquired from the field are used by control and optimization modules to increase the facility efficiency in terms of thermal comfort and energy consumption.

The study presented in [4] showed how the SportE2 optimization system can provide support to building managers in implementing energy efficient optimization plans. In [5], the same optimization system has been proved to be able to predict and optimize energy consumption and thermal comfort inside an indoor swimming pool. In that case a trained ANN was used to run in near-real time an optimization programme to provide the HVAC set-points for the maximum comfort with the minimum energy consumption according to indoor/outdoor thermal conditions. In particular, the indoor conditions were retrieved from field sensors installed in a swimming pool and the accuracy of the air temperature measured was the key parameter for the calculation of thermal comfort index used by the optimization engine. The same

* Corresponding author.
E-mail addresses: m.arnesano@univpm.it (M. Arnesano), gm.revel@univpm.it (G.M. Revel), f.seri@univpm.it (F. Seri).

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aspect was treated in a study presented in [6], which underlines that the application of HVAC control rules based on thermal comfort evaluation works well in air-conditioned spaces and could bring good energy saving potential. While [7] showed that a real bias on air temperature measure due to sensors density and placement on a zone can influence the model predictive control accuracy; they also observed that an accurate building inverse model can result in a model predictive control cost reduction of more than 13%. Revel and Arnesano [3] underlined as a detailed evaluation of the comfort level inside sport facilities spaces required a calibrated comfort model, where all the variables have to be measured inside the relative range of accuracy. Considering that [8] pointed out that the air temperature is one of the most influential variable on the comfort evaluation inside sports environments and considering the literature review reported in the previous paragraphs, the level of accuracy of the air temperature measure is a crucial task to address a 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 SportE2.

Stated the well-known problem about how important is the air temperature accuracy for the HVAC systems, now the attention should be moved to the issue of how the sensor network can be designed in order to obtain the maximum accuracy with the minimum deployment. This paper presents the development, application and validation in a real case study of a methodology to address that issue. The methodology is embedded in a software tool, called SOU (Sensor Optimization Unit), to be used by HVAC engineers on both new and existing buildings.

The same problem has been faced by recent studies, and the first step to optimize the sensor network is the knowledge of how the air temperature is distributed on the horizontal plane of a large space. Several studies already tried to characterize this spatial thermal distribution with different methods so to optimize the temperature monitoring, some using high level of detail (CFD or extensive sensors deployment), others using simplified models (zonal or sub-zonal models). The different approaches founded in literature are summarized in Table 1, where the key features of each study are reported to allow a comparison with the one proposed in this paper.

Considering the studies reported in Table 1 and the characteristics of sports environments, the following outcomes can be recognized:

- one of the main climate characterization in controlled spaces is the horizontal air temperature distribution;
- methodologies based on simulation or data driven approaches for the climate characterization of the space have to take into account the user profiling, external conditions as solar radiation, presence of neighbour spaces, shadowing elements and seasonal climate variation. The selected approach has to dynamically follow the indoor temperature variations due also to HVAC layout and climate control actions allowing to capture the seasonal thermal behaviour variations of the space with at least hourly frequency;
- methodologies based on simulation approach need of a higro-thermal model to take into account also indoor relative humidity, a significant parameter in sport spaces, due to presence of swimming pool and people practising sport;
- the typical measurement infrastructure for HVAC control is a single point thermostat placed on the perimeter of the space or a single temperature sensor on the return duct;
- the typical sensor network installation for thermal characterization of large spaces is made by a widespread of temperature sensors, taking into account the possible barriers for sensor installation;
- the sensor optimization placement algorithms founded in the proposed studies are based on different approaches, highlighting the missing of a unique recognized criteria.

Looking at Table 1, the consequent outcomes and the methodologies to reproduce the temperature distribution, it is correct to say that CFD

Table 1
Literature review of key features.

References	Large/small room	Measured ambient parameters for climate characterization	Approach	Drivers for sensors selection and density	Outcome
[9]	Large room	Weather, thermal comfort level, air changes rates, CO_2, air temperature vertical stratification.	CFD	Comfort evaluation	Development of various potential strategies for natural and low energy conditioning.
[10]	Large room	Horizontal air temperature distribution.	CFD	CFD model calibration	HVAC performance evaluation based on horizontal air temperature distribution; sensor positioning based on undefined criteria.
[11]	Small room	Vertical and horizontal air temperature distribution.	CFD	CFD model validation and comparison of different air temperature monitoring approaches	Development of a methodology for optimal air temperature monitoring based on measured data + CFD.
[12]	Small room	3D air temperature distribution from MINIBAT test cell experiment and simulation.	Zonal model	Model validation	Development of a novel modelling approach, optimal sensor positioning linked with optimal room heating control.
[13]	Small room	Outdoor air temperature, humidity, solar radiation intensity, speed and wind direction and indoor air temperature in the reference room.	ESP-r	Model calibration and validation	Evaluation of the impact of sensor placement on the heating thermal consumption and thermal comfort in a room.
[14]	Small room	Air temperature vertical stratification.	Zonal model	Model validation	Comparison between the mean air temperature value and the air temperature retrieved by sensors placed at different heights.
[15]	Large room	Spatial thermal distribution (25 temperature sensors), rate and temperature of air flow 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.
[16]	Large room	Horizontal air temperature distribution (54 air temperature sensors), relative humidity, light level.	–	Data mining to understand distribution of environmental parameters	Development of methodology to predict temperature map of the space.
[17]	Small room	Spatial air temperature distribution, humidity and illuminance distribution.	–	Sensors reduction	Development of a methodology based on sensor clustering to reduce the number of sensor nodes.
[18]	Large room	RTUs supply and return air temperatures, external temperature.	CFD	Model validation	A retrofit analysis with respect to the change of the thermostat locations on both comfort (temperatures) and energy consumption.

model [9,10,11,18] "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 [19], but they are mostly used for steady-state computations, and hardly ever considered in system-level stud" as reported in [12]. For this reason, the studies [12,13,14] proposed a simplified methodology based on zonal model and use field measurement to calibrate and validate the model, making it able to optimize the sensor placement linked with the climate control of the space. However, although zonal models need less requirements compared with the CFD model, they are developed for small rooms with a specific domains of application making them limited for large Sport space studies with such a particular thermal behaviour. Finally, the data driven approach methodologies presented in [15,16,17] provides a very accurate reproduction of the indoor thermal behaviour of the space, but the requirement of an extensive installation of instrumentation measuring for long time period, makes this approach difficult to apply inside Sport Facilities spaces, due to their typical usage and layout (e.g. presence of a swimming pool), which represents a barrier for sensors deployment.

Considering the outcomes reported above, this paper investigates and demonstrates the approach included in the SOU, based on the sub-zonal breakdown of a large space. The entire space is divided in a reduced number of volumes so to retrieve easily the hourly temperature trends in each of them, with simulation modelling approach or field sensors for restrict data-driven approach. For the first case, an upgraded version of a well-mixed multi-zone modelling tool, known as HAMBase [20], was developed for the scope. The obtained temperature trends are used to determine the optimal sensors location through statistical analyses of the discrepancies among distributions estimated with different numbers of sensors in different locations (taking also into account measurement uncertainty). To this aim, the SOU optimization process proposes 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 Table 1, as it is focused on improving the measurement accuracy linked with positions and number of sensors.

The SOU includes those functionalities in the overall workflow that, starting from data input guided by simple user interface, provides the optimal sensors location and the corresponding measurement performance achievable. In this way, the optimization procedure can be applied easily by HVAC designers given the simplified input data driven approach and the low computational load. The objective of the proposed tool is to have an intermediate approach that reduces the complexity and costs of the CFD, avoids the extensive sensors installation found on the data driven approaches and exploits the advantages of the zonal approach. An additional advantage of the presented tool is the modularity. In fact, the optimization procedure does not depend on how the data are generated, so in the case of existing buildings both measured or simulated data sets can be used, while for new buildings, the tool can be used in the design phase using the simulation model that is generated with information commonly available in that phase (e.g. from Building Information Model).

This paper illustrates the complete methodology of the SOU, with particular focus on the key contribution given by the measurement performance index that relies on proven statistical methods/metrics and validated multi-zone modelling technique for well-mixed zones. A real application is also presented as case study, which is a large space with swimming pool sited in Cesano (Rome, Italy). In this case, the SOU is applied to re-design the existing measurement system. A temporary sensor network was installed in the swimming pool to investigate the presence of a horizontal temperature distribution, illustrate the data driven approach and to validate the results retrieved with the SOU. In this real application, the effectiveness of the proposed approach is evaluated with a comparison between performances of the existing measurement system and the new optimal one, with a quantitative analysis of the deviation from the maximum accuracy achievable, which is obtained with the temporary sensor network installed.

2. Description of the tool

2.1. General approach and methodology applied

This paper proposes a novel approach, based on a measurement performance index, to support HVAC engineer to optimize the air temperature monitoring, in terms of number of sensors and placement in large spaces. The methodology workflow is described in Fig. 1, basically it is composed by two main steps:

1. Dataset generation characterizing the horizontal air temperature distribution in the space, which is a key climatic condition that must be 'measurable' either 'physically'/'virtually' or both;
2. Optimization of sensors number and placement along the perimeter of the space.

The first one can be approached through simulation or measurement. In the case of simulation, a sub-zonal model divides the entire space horizontally in sub-volumes, which are equals volumes of air considered perfectly mixed. The model outcomes are temperature trends for each volume positioned on each central points of the sub-volumes; the model generates hourly temperatures trends covering a maximum period of one year. In the case of measurement, a sensor network installation is mandatory. The space is virtually divided in sub-volumes, then the temperature sensors have to be deployed at least one inside each sub-volume dividing the space, also depending on sub-volumes dimensions. Sensors are usually installed along the perimetral walls, due to layout constraints in Sport Facility. Once that the data are acquired for a defined time window, an interpolation function, based on the weighted inverse distance method, uses the retrieved data to calculate temperature trends on the central points of the virtual sub-volumes dividing the space.

In both cases, simulation or measurement, the sub-zones breakdown has to cover the space horizontally in order to generate volumes identical and homogeneously allocated. In the case of simulation, the user of the SOU fills the user interface (see Fig. 2), then the software automatically calculates the needed number and positions of sub-zones based on numerical requirements established by the solver of the simulation. While, in the case of data driven approach, the number of available sensors and positions defines the number and location of sub-zones.

Once that temperature trends are generated, the methodology proceeds with the optimization. The SOU calculates the most accurate value of temperature (reference temperature, Fig. 3) for the entire space as the mean of temperatures coming from the sub-zones (simulated or measured), considered as a temperature trend evaluated on a central node positioned at the middle of the entire volume, considered perfectly mixed. Then, the SOU calculates the mean temperature trends combining all the possible sub-zones temperatures coming from the previous step.

After that, the deviances between the reference temperature trend and each trend coming from the sub-zones combinations are calculated. These deviances represent the measurement errors due to sub-zones selection to cover the temperature monitoring task. Thus, each deviance is related to the sub-zone/sub-zones selected as possible optimal ones. The key novelty of the methodology is the optimal sub-zones selection process, which is based on a dedicated measurement performance

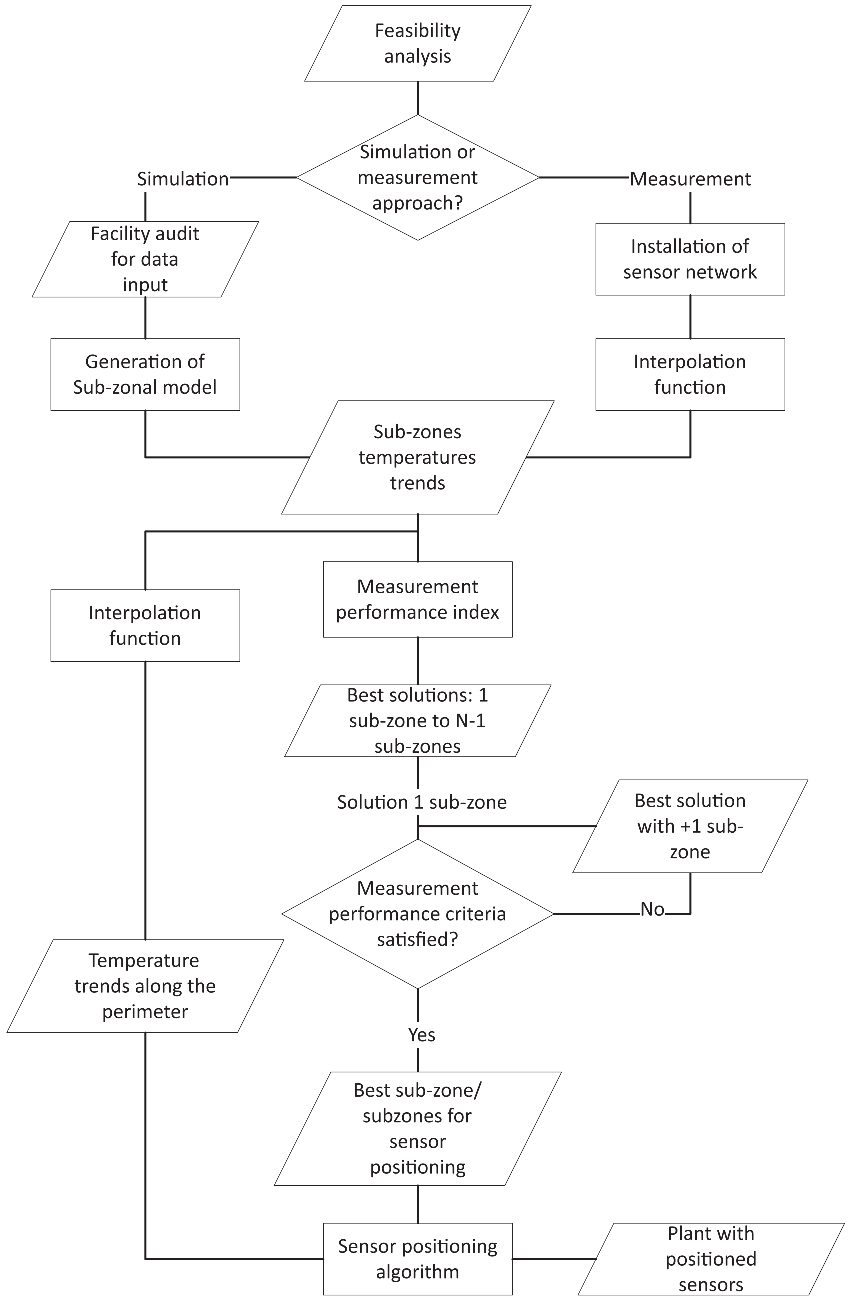

Fig. 1. SOU workflow.

index made by the sum of statistical features. In particular, each deviance is evaluated in terms of:

- Mean deviation, the tendency to over/under estimate the average temperature of the entire space. This characteristic is relevant to avoid waste of energy and discomfort in terms of overheating/overcooling;
- Standard Deviation, the final measurement uncertainty, that is fundamental for the optimal HVAC system regulation;
- Outliers, a measure of the amount of time during which the monitoring system is providing a value with an uncertainty higher than a fixed threshold (e.g. the sensor uncertainty provided by manufacturer);
- Z test, an indicator of the influence of external perturbations effecting the measurement.

The performance index is composed by the described statistics calculated for each deviance so to define the quality of each combination of sub-zones for the potential sensors deployment. Next, the software generates a ranking based on the score coming from the previous step. The process ends with the selection of optimal sub-zones where the installation of sensors will provide the required measurement performance according to pre-defined criteria. Once that the optimal sub-zone/subzones are selected, an interpolation function defines the optimal installation along the perimeter.

2.2. Dataset generation

To generate simulated dataset of temperature distributions in the space, a dedicated thermal modelling was developed, so to allow the

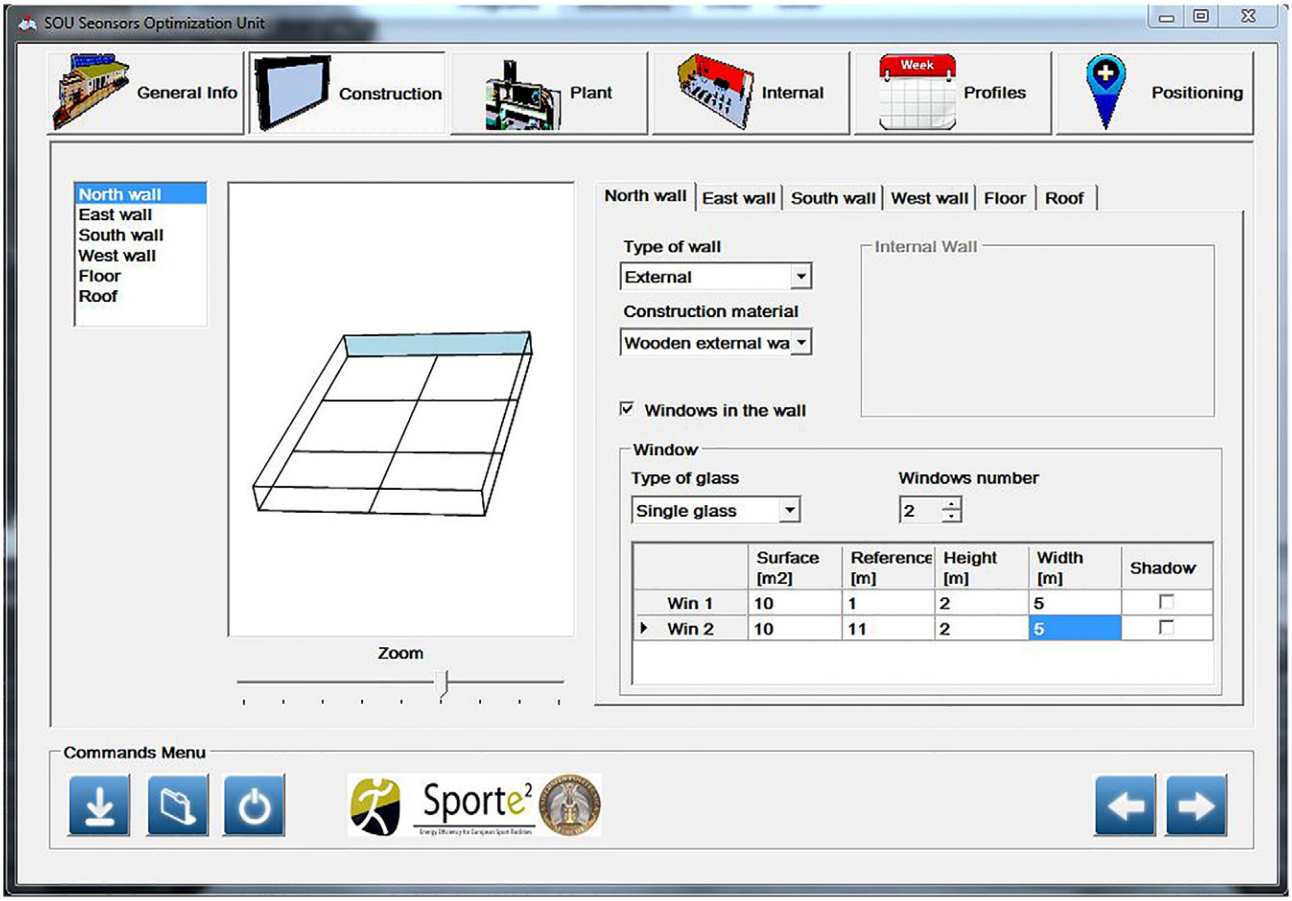

Fig. 2. User interface of the SOU.

macro discretization of the horizontal air distribution. The thermal model is based on the HAMBase library, that is an open library implemented in Matlab computing environment. It simulates the hourly indoor air temperature and humidity of a multi–zone building with a relatively small mathematical computational requirement. The HAMBase has been already applied for air temperature prediction, also in indoor swimming pool, and overcame the ASHRAE test [23]. De Wit described extensively the physics of this model in [20]. 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 value of the whole space. The sub-zonal approach can overcome the lack of resolution of the multi-zone approach. Moreover, the HAMBase is an open library useful when customizations of the code are needed. In fact, in order to develop a sub-zonal approach this feature is required to split a single zone approach in a certain number of sub-zones or to distribute thermal loads in a discretized volume. The developed customization of the hygro-thermal model divides the space, which would normally be a single zone, into a coarse network of smaller sub-zones, as shown in Fig. 3. Each sub-zone has to satisfy the hygro-

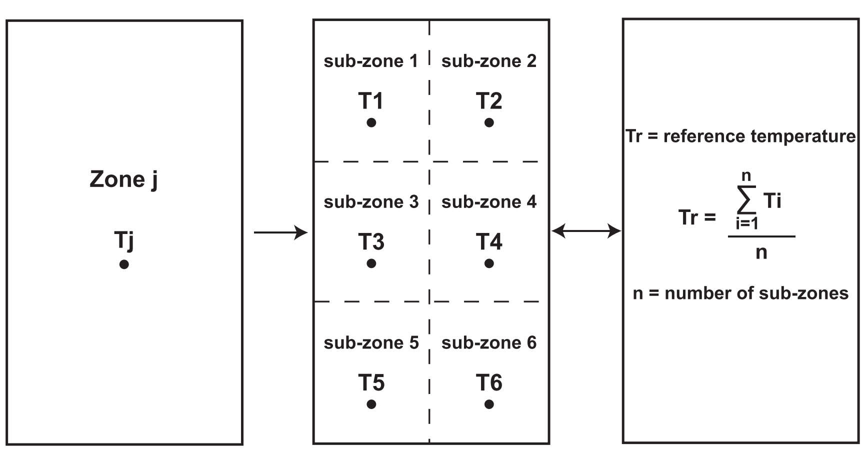

Fig. 3. From zonal model to sub-zonal model and calculus of reference temperature.

thermal and the inter-zonal airflow models, then the air contained inside the sub-zone *i* of the zone *j* is assumed to be perfectly mixed. The developed model allows an increase of resolution to characterize the air temperature distribution on the horizontal plane of the space. This approach permits the thermal characterization of the space evaluating the temperature gradients trends between the sub-zones allowing an optimization of the air temperature measure inside the space.

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 interval. The simplified approach of the proposed tool allows the problem setup with low computational load for a user that has not specific technical expertise (as required for a CFD). It also allows the possibility to simulate the thermal behaviour of an environment during one-year period, taking into account weekly use profile of the environment, 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.

The same characterization of the thermal environment can be done through the installation of a sensor network. In this case, nodes should be placed so to replicate the sub-zones breakdown, as generated with the thermal model, and temperature trends should be acquired for a period long enough to capture the typical usage profile. In fact, apart from the external thermal conditions, the indoor thermal distribution depends on the room usage (HVAC start and stop, set-points, occupancy and activity).

2.3. Optimization

The optimization objective is the minimization of sensors number able to provide the minimum deviation from the measurement performed by reference condition, one sensor in each sub-zone. To this aim, the optimization solver receives the simulated or measured temperatures dataset, as shown in Fig. 1, evaluates the measurement performance of sensor network including numbers and positions against the reference temperature that represents the uncertainty due to the sensors positioning and determines the optimal installation points.

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 gathered 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 each sensor.

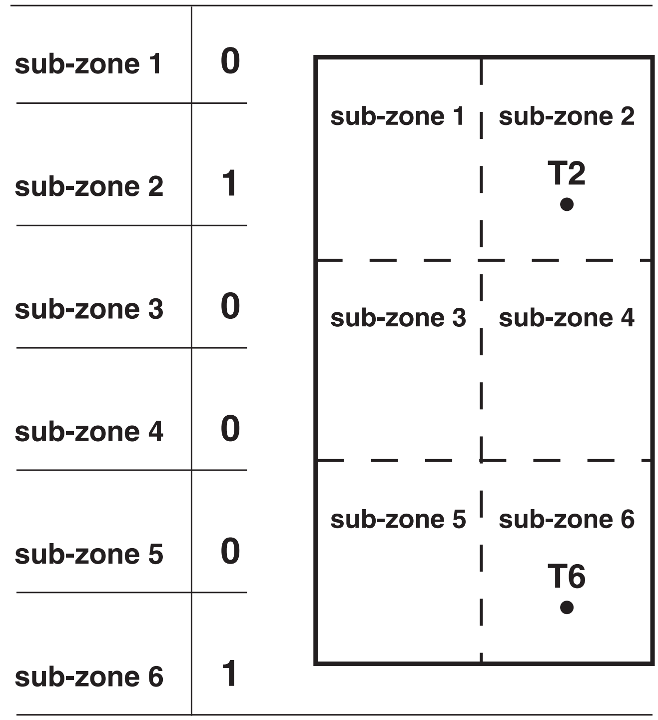

Fig. 4. Sensor network representation as bit string.

2.3.1. Measurement performance evaluation

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 and 0 if not. Each sensor network configuration can be represented as a row vector with the sensors positions, 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.

The deterministic solver generates all the possible installation solutions (a 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. Each combination is compared to the reference condition (a string of ones) which temperature

Table 2
Scores deviance assignment process.

Deviance ID	Ranking (R)	Mean deviation	Score (S_1)
16	1°	0.1 °C	$S_1(16) = (2^{n-1} - R + 1)$
35	2°	0.15 °C	$S_1(35) = (2^{n-1} - R + 1)$
…	…	…	…
3	2^{n-1}°	1 °C	$S_1(3) = (2^{n-1} - R + 1)$
Deviance ID	**Ranking (R)**	**Std deviation**	**Score (S_2)**
18	1°	0.12 °C	$S_2(18) = (2^{n-1} - R + 1)$
43	2°	0.24 °C	$S_2(43) = (2^{n-1} - R + 1)$
…	…	…	…
2	2^{n-1}°	1 °C	$S_2(2) = (2^{n-1} - R + 1)$
Deviance ID	**Ranking (R)**	**Outliers**	**Score (S_3)**
15	1°	1	$S_3(15) = (2^{n-1} - R + 1)$
56	2°	3	$S_3(56) = (2^{n-1} - R + 1)$
…	…	…	…
8	2^{n-1}°	681	$S_3(8) = (2^{n-1} - R + 1)$
Deviance ID	**Ranking (R)**	**Z index**	**Score (S_4)**
26	1°	0.6	$S_4(26) = (2^{n-1} - R + 1)$
38	2°	1.2	$S_4(38) = (2^{n-1} - R + 1)$
…	…	…	…
3	2^{n-1}°	8	$S_4(3) = (2^{n-1} - R + 1)$

Table 3
Selection of the best sub-zones configurations based on maximum I_m.

No sub-zone	Deviance ID	I_m
1	**5**	**206**
	12	162
	…	…
	3	23
2	**14**	**302**
	23	240
	…	…
	17	168
–	…	…
	…	…
	…	…
	…	…
n − 1	**27**	**358**
	19	315
	…	…
	41	235

profile T_r is calculated as the mean value of the n sub-zones temperature profiles:

$$T_r = \frac{\sum_{i=1}^{n} T_i}{n} \tag{1}$$

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

$$E = T_{solution\_set} - T_r \tag{2}$$

where $T_{solution\_set}$ is each temperature profile of the 2^{n-1}, provided by the combination of sensors and calculated as the mean value of the temperature profiles of each sub-zone included in the combination. Once calculated the deviations E for all possible combinations, their statistics, (mean deviation, standard deviation, outliers, Z index), are evaluated.

All the combinations are ranked according to each statistic and receive a score (S) equal to the position occupied in each ranking (Table 2).

A sum of the scores achieved in each ranking provides the performance index (I_m) for the configuration, calculated as following:

$$I_m = S_1(E) + S_2(E) + S_3(E) + S_4(E) \tag{3}$$

where S_1 is the score for the mean, S_2 for the standard deviation, S_3 for the outliners and S_4 for the Z test.

Once that an I_m is assigned to each distribution of sensors, the algorithm groups the solutions in terms of sensors number and selects the solution that achieved the best score in each group. The output is a number n of solutions with the respective performance index (Table 3).

The best sensors configuration, among the available, is the one that fulfils the defined criterion. The standard deviation, that represents the resulting measurement uncertainty of the configuration, has to be lower than sensing device uncertainty.

2.3.2. Sensor positioning algorithm

The first step of optimization identifies the sub-zones, where sensors should be installed. The nodal approach, adopted by the thermal model or measure, 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. In fact, sports environments present constraints for network deployment and sensors cannot be placed in the centre. Especially in swimming pools, where sensors can be placed only on the perimetral 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 [21,22], the perimetral temperatures values are calculated using an interpolation function based on the inverse distance weighting method [21] to obtain the required increase of temperature spatial resolution. The algorithm takes as inputs the temperature trends coming from the n sub-zones, the positions of these n source points are fixed as central node (Fig. 5) for each sub-zone that composes the entire space. The temperatures at the destination points (temperature nodes along the perimeter that are the potential physical points of installation, Fig. 5) 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 position that provides a temperature with the minimum

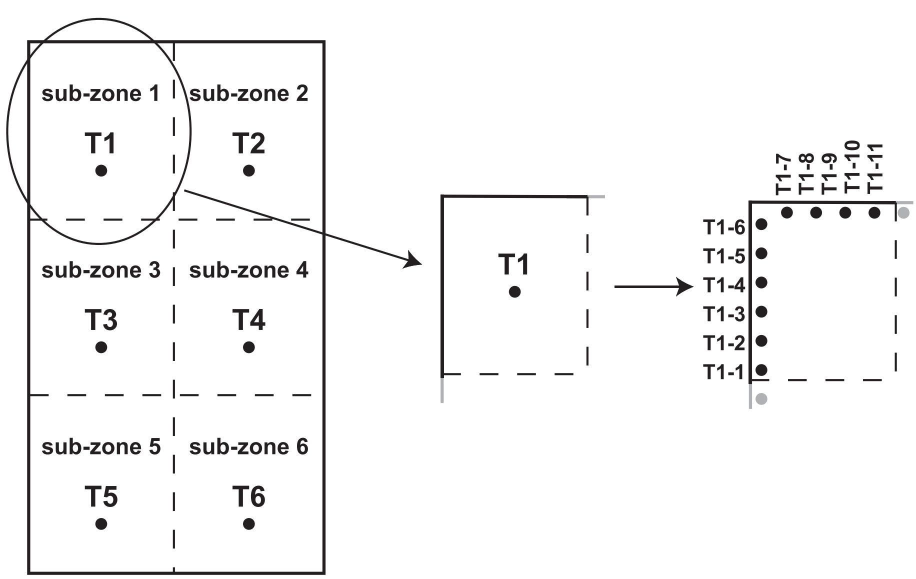

Fig. 5. Sub-zone positioning algorithm.

root main square error (*RMSE*) with respect to the sub-zone central temperature.

3. Validation and analysis of results

3.1. Description of the environment used as case study

The SOU is a tool conceived to find the optimal temperature sensors positioning in large spaces of sports buildings, where the building orientation, the solar radiation and the quantity of glazed surface assume a fundamental role for the thermal loads and temperature distribution in the environment. The swimming pool area of Fidia sports center, sited in Cesano (Rome) (Fig. 6) presents 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 and a minimum of 3 m. There are two swimming pools: adult pool with a surface of 312.5 m^2, and children pool of 75 m^2, 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 Fig. 6, the air is supplied from the left side of the central duct, and 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

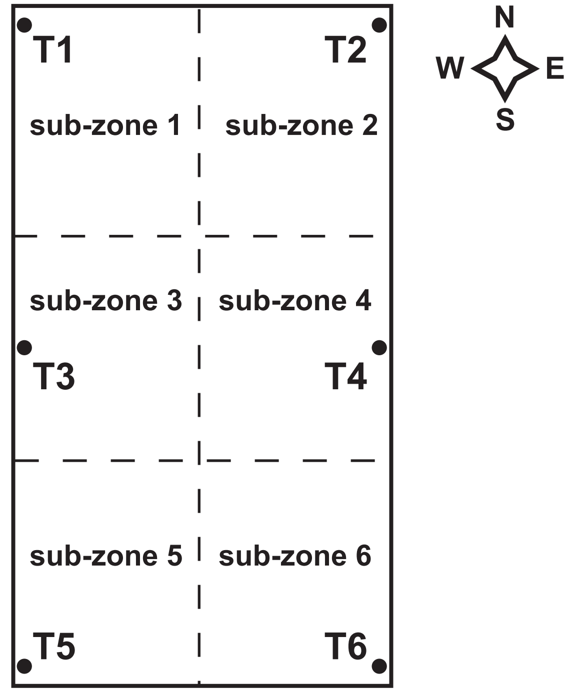

Fig. 7. Sensor network placement.

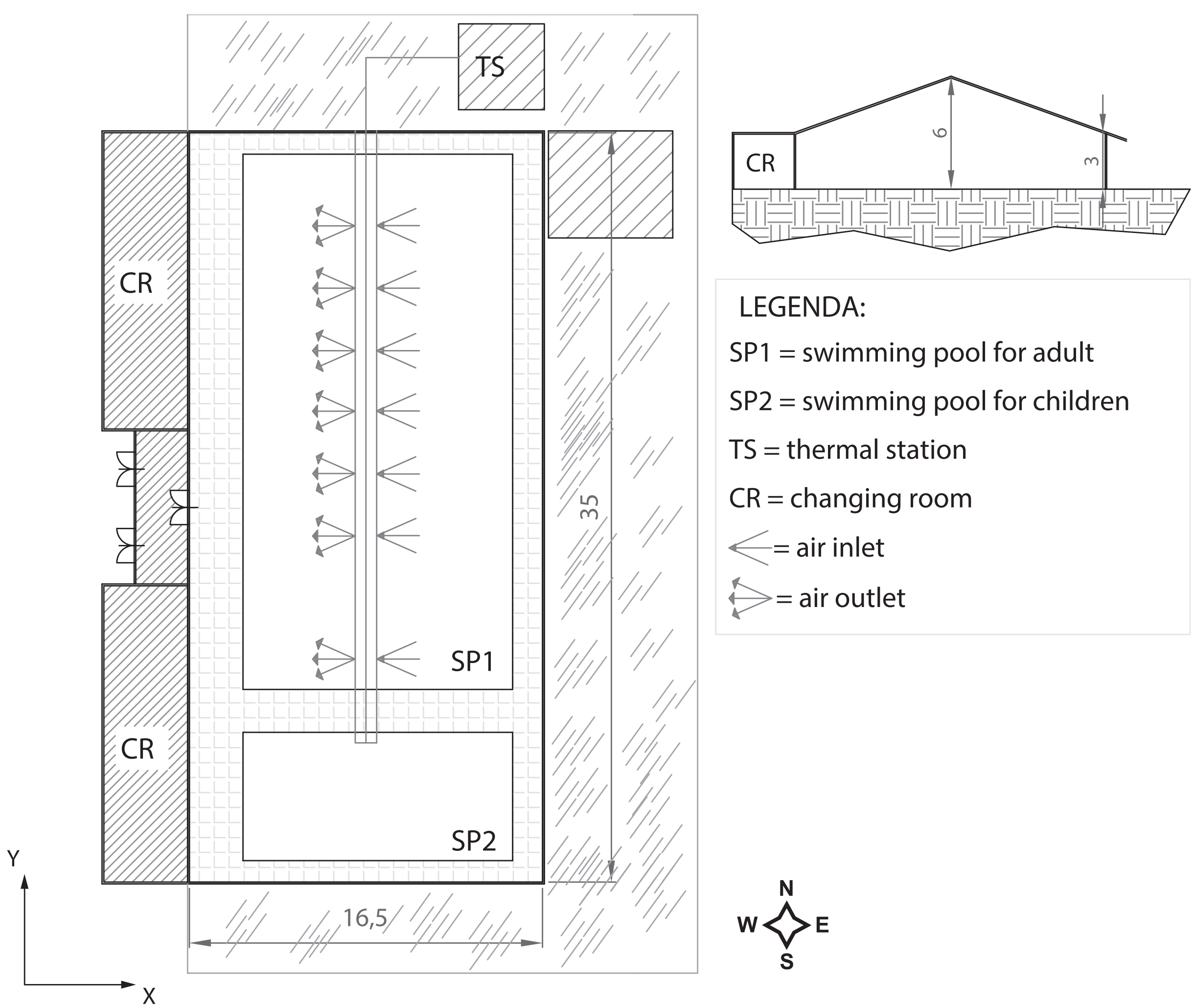

Fig. 6. General scheme of the indoor swimming pool in Fidia.

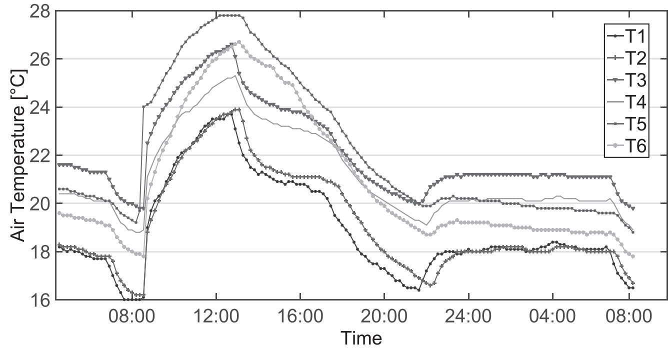

Fig. 8. Air temperature distribution inside the Fidia swimming pool.

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 ±0.5 °C and resolution of ±0.05 °C. The relative humidity sensors were capacitive transducers with an accuracy of ±5% and resolution of ±0.1%. The sensors placement (Fig. 7) 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 m from the ground, the same height of the existing thermostat.

Fig. 8 shows the 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 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. 8). Moreover, it can be seen that, when *T*1 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.

Table 4
Comparison of the statistical features between the measured and simulated optimal solutions.

	Simulated data	Measured data	Range
Mean	0.02 °C	0.04 °C	[0–1] °C
Std	0.3 °C	0.4 °C	[0–1] °C
Outliers	11	11	[0–681]
Z index	0.5%	1%	[0–100]%

3.2. 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 Section 3.1, 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. 9 reports the quality of the solutions expressed in percentage of satisfaction of the I_m on the y-axes and the number of sensors used on the x-axis. 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). In particular, considering that the worse *Std* score corresponds with 1 °C of standard deviation, the solution with three sensors reduced it to 0.4 °C (Table 4). This value is lower than sensor uncertainty (±0.5 °C) and the use of an additional sensor would increase the performance of the monitoring system by 3.7%, starting from a value of 88% (Fig. 9). Therefore, the implementation of an additional sensor is not justified by this little increase of performance, so the solution with three sensors is the optimal one, according to the criterion described in paragraph 2.3.1. Concerning the sensors positioning, they should be installed inside the sub-zones signed as numbers 1, 3 and 6 in Fig. 7.

Again, looking at the comparison between the optimization results retrieved with simulated and measured datasets in Fig. 9, a satisfactory correspondence was found. In fact, the simulation replicated the

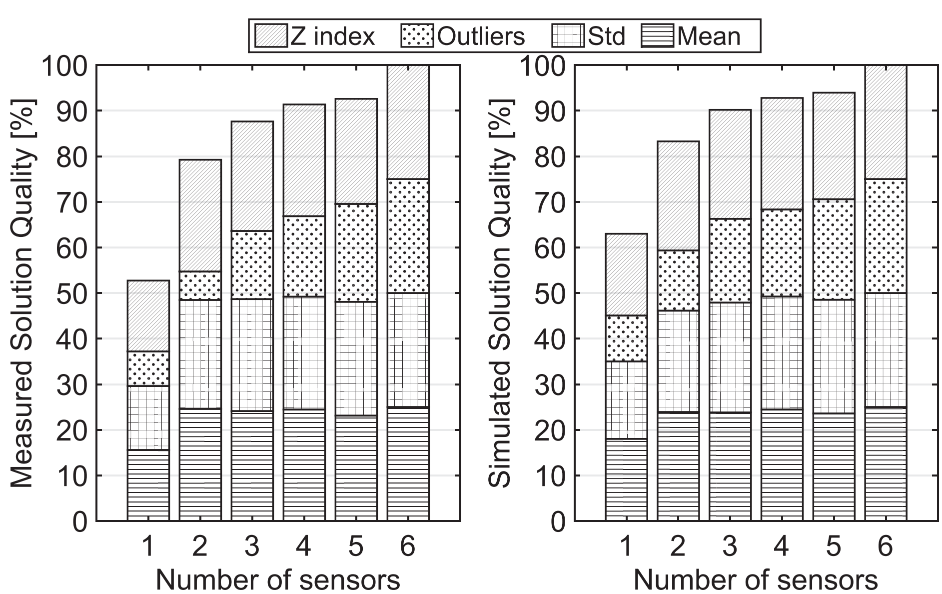

Fig. 9. Quality indexes of the measurement (left figure) and simulated (right figure) solutions using measured data.

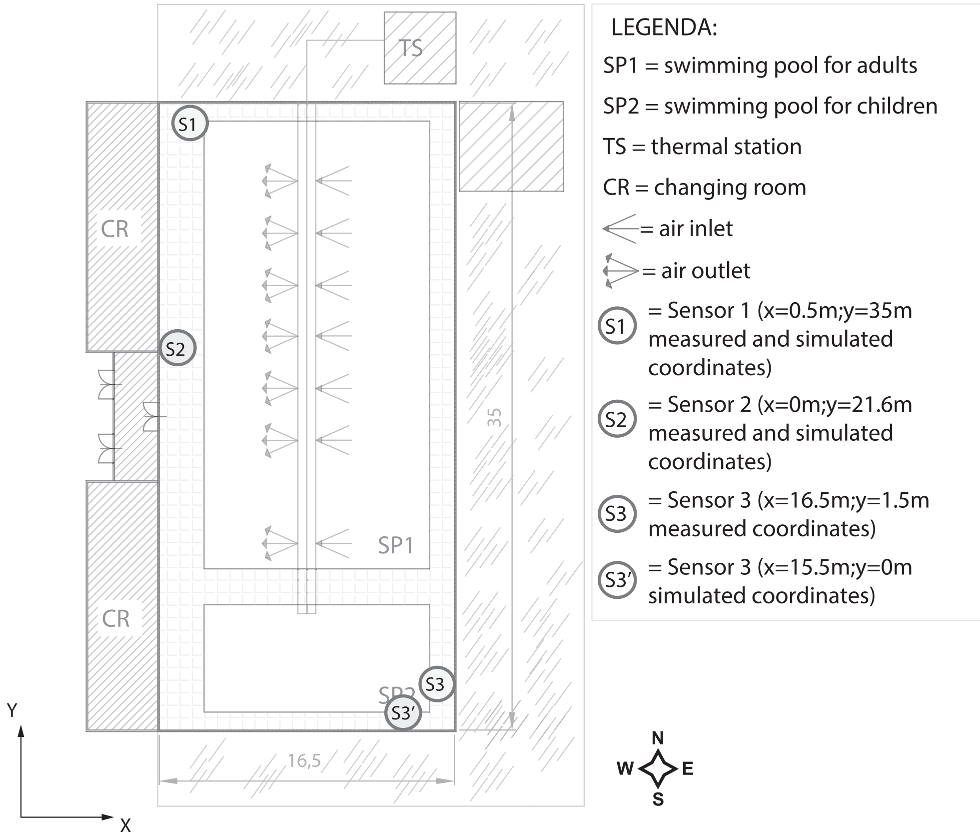

Fig. 10. Optimal sensors location retrieved with simulated and measured datasets of temperature.

measurement error in terms of statistical indexes and positions. 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. 9). Therefore, this solution can be considered the optimal one as shown by applying measured data.

Table 4 presents details about the comparison of statistics, used to calculate the performance index, between the optimal solutions retrieved with measured and simulated data.

The comparison showed the capability of the SOU to reproduce the temperature measurement performance related to 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.

3.3. Sensors 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 2.3.2, 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. 10.

A second phase of validation was performed to compare the temperature measured 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 m. The measurement system was composed of thermocouples type K (calibrated in controlled environment to obtain an accuracy equal to ±0.3 °C), an acquisition module and a PC for data logging. The results shown in Fig. 11 demonstrate the capability of predicting the perimetral air temperatures by the SOU modelling component. The simulated trend followed the measured one along the whole perimeter and this is fundamental because the

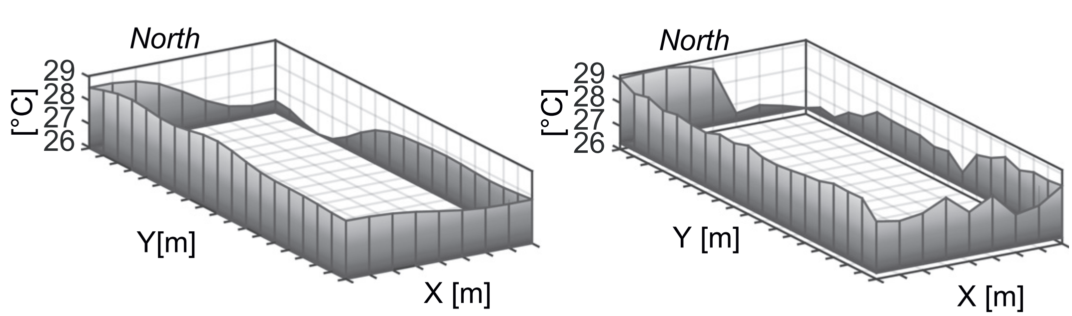

Fig. 11. Simulated (left side) and measured (right side) air temperature trend along the perimeter.

Table 5
Statistical characteristics of simulated and measured air temperature trends along the perimeter.

	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

following optimization process relies on the accuracy achievable from the prediction obtained.

Basic statistical characteristics regarding the simulated and measured air temperature trends along the perimeter are reported in Table 5. 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.

4. Impact of the proposed tool

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. 7, 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 (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. 12.

The comparison showed that the measurement error decreased from a mean value of 0.6 °C to 0.1 °C with a 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. Conclusion

The paper introduced the SOU, a tool to decrease the air temperature measurement uncertainty in large spaces. The theory behind the software was explained in the first part of the paper, where a modified version of the HAMBase with sub-zonal division was developed. Then, it was coupled with an optimization solver to calculate the optimal location of the air temperature sensors. The second part of this work was dedicated to the application of the tool to a sports facility with 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 0.13 °C and only 1.5% of the live time.

The SOU is a stand-alone software with low computational requirement (minimum 1.5 GHz processor and 2 GB RAM) and the whole process can be performed in ten minutes, including input data. The current version is the first step towards the definition of the optimal placement of temperature sensors inside large sports facilities areas. The paper described the entire methodology which the SOU is based on, showing also the application and the validation of the tool in a real test case. The tool was developed and applied to sports facilities, but other buildings present the same issue concerning the air temperature distribution and the consequent need to design a sensor network able to reduce the measurement uncertainty. Thus, the SOU will be applied to other type of environments allowing a generalization of the proposed approach. To this aim an analysis of the key thermal perturbations should be performed in order to extend the capacity of reproducing the thermal distribution of the space, which has been easier in sports facility where there are well-defined thermal loads (e.g. swimming pool, big fan coils, zones where occupants are performing exercise etc.). This initial application was useful to validate the overall system but also to provide basis for its replication.

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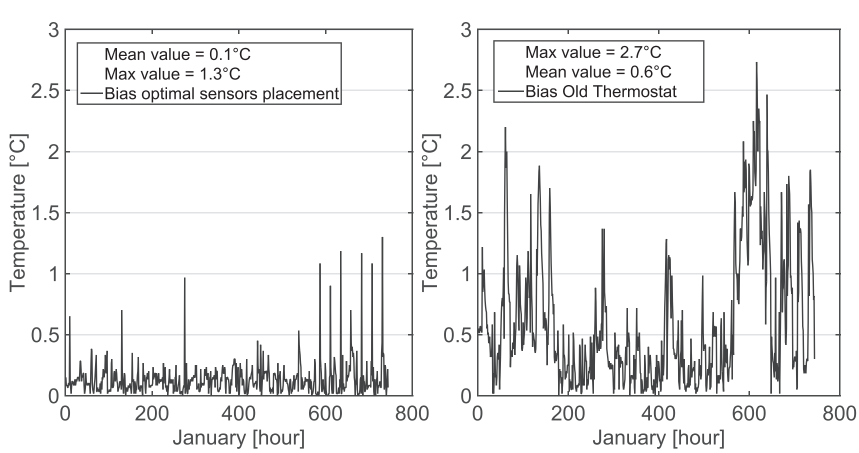

Fig. 12. Comparison between the old thermostat and the new optimal bias due to sensor placement for temperature monitoring.

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