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An inversion strategy for energy saving in smart building through wireless monitoring

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Abstract. The building plants represent one of the main sources of power consumption and of greenhouse gases emission in urban scenarios. The efficiency of energy management is also related to the indoor environmental conditions that reflect on the user comfort. The constant monitoring of comfort indicators enables the accurate management of building plants with the final objective of reducing energy waste and satisfying the user needs. This paper presents an inversion methodology based on support vector regression for the reconstruction and forecasting of the thermal comfort of users starting from the indoor environmental features of the building. The environmental monitoring is performed by means of a wireless sensor network, which pervasively measures the spatial variability of indoor conditions. The proposed system has been experimentally validated in a real test-site to assess the advantages and the limitations in supporting the management of the building plants towards energy saving.

1. Introduction

The need of more energy efficient and sustainable buildings has gained more and more attention in the last decades. Climate changes like the increasing global temperatures and the weather alterations are considered some of the consequences of the gas emissions originated by the combustion of fossil fuel. The energy generation from renewable resources and a more accurate management of consumptions are often imposed to limit the impact on the environment.

Private and public buildings are responsible of about one third of the urban energy consumptions [1][2]. Therefore, it is evident that the optimization of energy usage at building level would significantly impact on the power demand. Toward this end, besides the introduction of new materials and more efficient construction strategies, one of the main requirements is to know how the building systems behave and their effects on the satisfaction of the end-users.

Among the innovative solutions for the distributed monitoring of indoor spaces, the wireless sensor network (WSN) technology is suitable for the scalable and low-cost measurement of heterogeneous environmental parameters. The potentialities of this wireless technology have been verified in a huge number of indoor/outdoor applications.

State of the art examples include WSN-based architectures for smart home applications [3][4], and wireless sensors for the monitoring of appliance consumptions and schedule in residential apartments [5]. Similar WSN platforms have been also exploited for the localization and tracking of both passive [6]-[8] and active [9] targets. Additional information about the indoor occupancy level has been also estimated from the analysis of environment perturbations [10].



The building information that can be measured with WSN nodes become fundamental for the evaluation of the key performance indicators (KPI) related to the quality of the indoor environment and the consequent user comfort. The changes in the KPI behaviour are mainly due to the weather conditions and to the functioning of the heating-ventilation-air-conditioning (HVAC) systems [11][12]. The standard control strategies of HVAC systems are based on measurement of local temperature probes and aim to preserve a predefined value or preconfigured temperature masks. Such an approach does not consider predictive control schemes to address demand-side flexibility (e.g., short-term variations like weather changes or indoor occupancy).

In this paper, a learning-by-example (LBE) inversion strategy based on support vector regression (SVR) is aimed at reconstructing the desired thermal comfort KPI [the predicted mean vote (PMV) [13] has been considered as standard comfort indicator] from the environmental conditions. The method exploits the weather forecasts for the short-term prevision of outdoor changes, which impact on the indoor conditions. The output of the approach provides the target temperatures that satisfy the PMV requirements. Accordingly, the HVAC system can be calibrated in order to optimize the problem unknowns (i.e., the indoor environmental parameters).

The proposed solution has been validated in a real test field using environmental measurements acquired by a WSN prototype and by a weather station installed in proximity of the building. A selected set of preliminary results are presented to show the capability to learn and forecast the indoor thermal conditions subject to the KPI requirement.

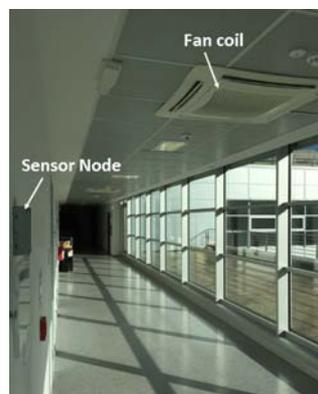
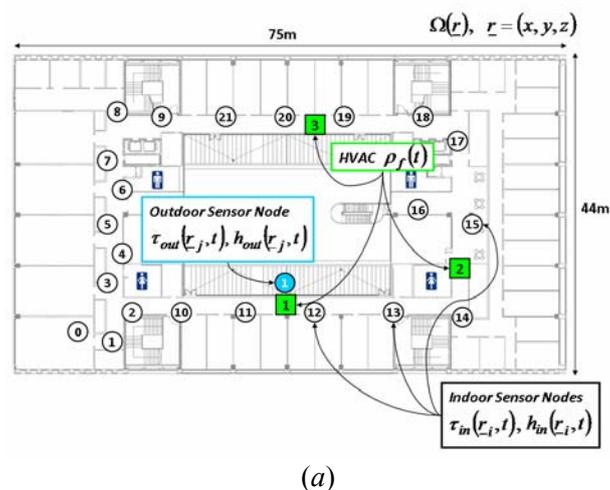


Figure 1. Investigation domain and system deployment: (a) floor map and node position, (b) real scenario.

2. System Architecture

Let us consider a WSN deployed in the three-dimensional domain $\Omega(\underline{r})$, $\underline{r} = (x, y, z)$ being the position vector. The WSN is composed by a set of $N = N_{in} + N_{out}$ nodes in positions \underline{r}_i^{in} , $i = 1, \dots, N_{in}$, and \underline{r}_j^{out} , $j = 1, \dots, N_{out}$, where N_{in} is the number of indoor nodes and N_{out} the number of nodes installed outdoor.

The outdoor nodes provide the reference environmental condition and together with the weather station allow the estimation of the complex ‘indoor-outdoor transfer function’ determined by the building properties. It has to be noticed that the weather station provides also the forecast of the outdoor temperature.

The WSN nodes are equipped with multiple sensors for the acquisition of the environmental parameters including the temperature $\tau_{in}(\underline{r}_i, t)$ and $\tau_{out}(\underline{r}_j, t)$, and the humidity $h_{in}(\underline{r}_i, t)$ and $h_{out}(\underline{r}_j, t)$, where t is the time instant of the data acquisition.

A finite set of F fan coil units are installed in known positions \underline{r}_f , $f = 1, \dots, F$, as part of the HVAC system. The on/off working schedule of the fan coils is controlled by the main building management system and it is defined by the binary functions $\rho_f(t) = \{0, 1\}$, $f = 1, \dots, F$ [$\rho_f(t) = 1$ if the f -th fan is active, $\rho_f(t) = 0$, otherwise].

Starting from the indoor environmental parameters, the comfort indicators $PMV(\underline{r}_i, t) \in [-3; +3]$, $i = 1, \dots, N_{in}$, are computed according to the formulation reported in [14]. It is worth noting that the PMV indicator includes additional parameters like the air velocity and the clothing insulation (more difficult to be measured and often initialized with reference values) to provide an evaluation of the comfort ranging from the cold [$PMV(\underline{r}, t) = -3$] up to the hot [$PMV(\underline{r}, t) = +3$] thermal sensation, passing through the ideal comfort value $PMV(\underline{r}, t) = 0$.

The proposed SVR-based learning technique is aimed at estimating the relation between the indoor and the outdoor environmental conditions in order to successively exploit weather forecast for the prevision of indoor conditions in the building positions \underline{r}_i , $i = 1, \dots, N_{in}$. Toward this end, a set of regression functions $\Psi_{i,j}$, $i = 1, \dots, N_{in}$, $j = 1, \dots, N_{out}$ are trained for each i - j couple of nodes (a total of $N_{in} \times N_{out}$ functions are obtained) starting from the knowledge of the known samples (called training sets)

$$\left\{ \left[\tau_{out}(\underline{r}_j, t), h_{out}(\underline{r}_j, t), PMV(\underline{r}_i, t), \rho_f(t), \tau_{in}(\underline{r}_i, t) \right]_{(i,j)} ; t = 1, \dots, T \right\} \quad (1)$$

acquired at T different and representative time instants.

The function $\rho_f(t)$ is selected according to the rule $\min_f \left[|\underline{r}_f - \underline{r}_i|^2 \right]$ in order to select the fan coil closer to the measurement node. After the training phase, the regression functions

$$\Psi_{i,j} : \left[\tau_{out}(\underline{r}_j, t), h_{out}(\underline{r}_j, t), PMV(\underline{r}_i, t), \rho_f(t) \right] \rightarrow \tau_{in}(\underline{r}_i, t) \quad (2)$$

are defined and successively exploited to estimate indoor temperatures at any point in time $t = t + \Delta t$, where Δt is the forecasting period. Moreover, it has to be noticed that the input feature $PMV(\underline{r}_i, t)$ can be used as requirement of the desired comfort in position \underline{r}_i .

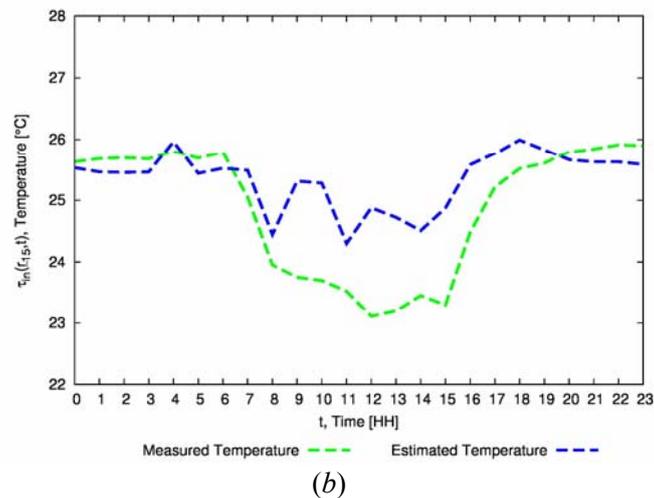
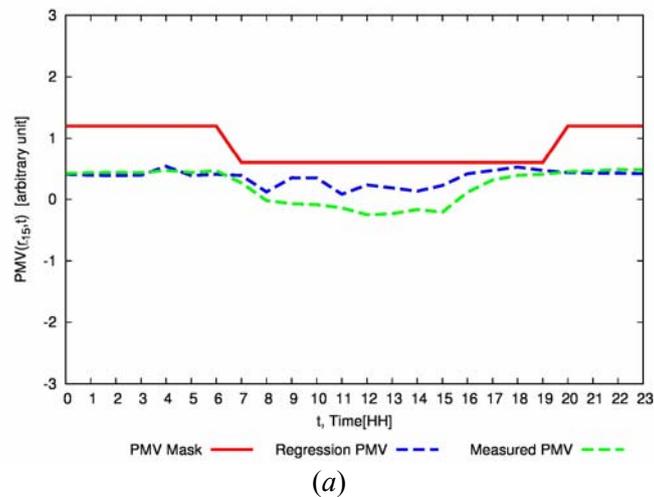


Figure 2. Summer period. (a) PMV mask vs measured and regression PMV. (b) measured vs estimated temperature.

3. Experimental Validation

The proposed system has been experimentally validated in a real test site at the ELEDIA Research Center of the University of Trento, Italy. More in detail, $N_{in} = 21$ sensor nodes distributed within $\Omega(\underline{r})$ at height $z_i = 2m$, $i = 1, \dots, N_{in}$ have been considered for indoor data acquisition. As regards the outdoor parameters, $N_{out} = 1$ node has been deployed. All the WSN nodes are equipped with SHT21 temperature and humidity sensors. Additional details about the wireless network architectures for smart home monitoring and management are reported in [3]. A long-term measurement campaign has been performed in order to collect environmental information in different seasons. Starting from such indoor features, the corresponding PMV indexes have been calculated.

Concerning the HVAC system, $F = 3$ representative fan coils have been monitored to extract the binary functions $\rho_f(t)$. For the sake of simplicity, the working schedule of the $f = 1, \dots, F$ fan coils is assumed equal.

The SVR methodology has been trained considering a set of $T = 216$ data samples acquired at different day and night hours, and both in Winter and in Summer periods. As a preliminary

experiment, one regression function $\Psi_{15,1}$ related to the nodes $i = 15$, $\underline{r}_{15}^{in} = (x_{15}^{in}, y_{15}^{in}, z_{15}^{in})$ and $j = 1$, $\underline{r}_1^{out} = (x_1^{out}, y_1^{out}, z_1^{out})$ has been trained.

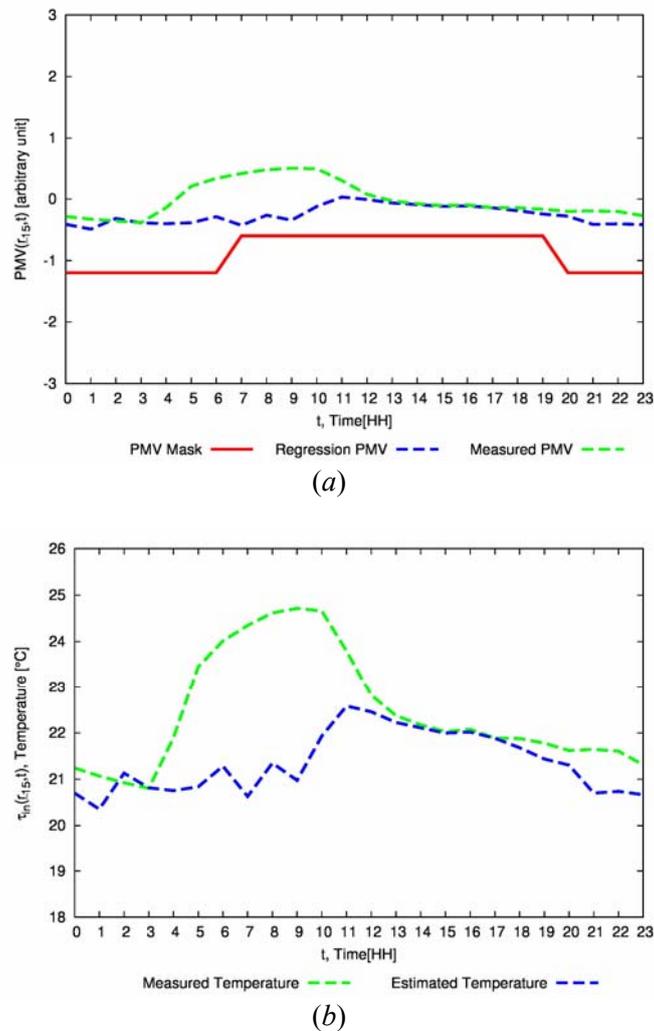


Figure 3. Winter period. (a) PMV mask vs measured and regression PMV. (b) measured vs estimated temperature.

During the test phase, the desired *PMV* daily mask has been defined and given as input feature of the test dataset. Different *PMV* masks have been designed for the summertime [Fig. 2(a)] and for the wintertime [Fig. 3(a)]. The objective of such comfort masks is to impose a daily comfort level that satisfies the user need in the desired time windows.

In order to validate the forecasting capability of the proposed approach, the outdoor parameters $\tau_{out}(\underline{r}_1, t)$ and $h_{out}(\underline{r}_1, t)$ with $t = t + \Delta t$, and $\Delta t = 6h$, have been adopted exploiting the outdoor weather station. Such values have been used to create the test dataset. The obtained estimations of the predicted *PMV* are shown in Fig. 2(a) and Fig. 3(a) for the Summer and the Winter tests, respectively. The comparison with the measured *PMV* (i.e., the comfort obtained without the application of the proposed method) points out that the imposition of the comfort masks has caused higher (in Summer) and lower (in Winter) *PMV* values, closer to the desired and more energy-efficient values. Accordingly, the corresponding indoor temperatures are shown in Fig. 2(b) and Fig. 3(b).

4. Conclusions

In this paper, a novel methodology for the estimation and forecasting of thermal comfort in smart buildings has been proposed. The energy efficiency of HVAC systems has been addressed through the imposition of desired PMV masks. The corresponding indoor temperatures have been estimated as energy-efficient suggestion for the building management systems. The obtained results have shown the generalization capability of the SVR-based learning approach when dealing with real environmental measurements. Current activities are focused on the integration of location-based information about the user presence and behaviour within the monitored environments, in order to improve the management of HVAC plants according to the actual user needs. The wireless localization solutions presented in [3] will be exploited using the same wireless architectures adopted for environmental monitoring.

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