Crowdsensing for a sustainable comfort and for energy saving

Original

Crowdsensing for a sustainable comfort and for energy saving / Cottafava, D.; Magariello, Stefano; Ariano, Rosy; Arrobbio, O.; Baricco, M.; Barthelmes, V.; Baruzzo, G.; Bonansone, M.; Console, L.; Contin, L.; Corgnati, S.; Dotta, S.; Fabi, V.; Gambino, P.; Gerlero, I.; Giovannoli, A.; Grillo, P.; Guaschino, Guido; Landolfo, P.; Malano, M.; Mana, D.; Matassa, A.; Monterzino, L.; Mosca, S.; Nuciari, M.; Olivetta, E.; Padovan, D.; Panto', Eleonora; Rapp, A.; Sanseverino, Marialuisa; Sciullo, A.; Sella, S.; Simeoni, R.; Tartaglino, Andrea; Vernero, F.. - In: ENERGY AND BUILDINGS. - ISSN 0378-7788. - 186:(2019), pp. 208-220. [10.1016/j.enbuild.2019.01.007]

12 November 2024

Post-print version of

Cottafava, D., Magariello, S., Ariano, R., Arrobbio, O., Baricco, M., Barthelmes. V., … & Vernero, F. (2019). Crowdsensing for a sustainable comfort and for energy saving. *Energy and Buildings*, 186, pp. 208-220. DOI: 10.1016/j.enbuild.2019.01.007.

Original version available at: https://www.sciencedirect.com/science/article/pii/S0378778818329955

Abstract

Energy efficiency in buildings is a key issue in the current energy transition. In order to reduce building energy consumption, users' behaviour and the perception of indoor environmental comfort must be taken into account; these aspects are inextricably linked to energy demand, consumption and related costs. In this paper, we present the methodological framework, technological solutions and outcomes of the ComfortSense project. ComfortSense aimed at decoupling energy demand from indoor comfort. We focused on Heating, Ventilating and Air Conditioning (HVAC) systems in buildings, on users' behaviour and on comfort perception by treating buildings as socio-technical systems. Our approach which was multidisciplinary and included the contribution of sociologists, physicists and computer scientists was based on Internet of Things technologies, on a Living Lab design and testing process and on a Crowdsensing approach. Physical parameters (objective variables), such as temperature, CO_2 concentration and relative humidity, were measured by a Wireless Sensor Network and by wearable devices, while the users' perception of comfort (subjective variables) were recorded as real-time feedback through a Mobile App in three pilot buildings of the University of Turin, engaging about a thousand buildings' users (professors, researchers, students and employees). Objective and subjective variables were correlated through an adhoc Direct Virtual Sensor. Thanks to the Direct Virtual Sensor forecasting we demonstrated that, adopting an adaptive indoor comfort management, users' comfort can be remarkably improved while reducing the energy consumption of HVAC systems.

1. Introduction

In the last decades, the European Union has begun a long path to reduce greenhouse gas (GHG) emissions. The building sector, despite the huge global effort from both the governance and the international academic community, still remains one of the most impactful; in fact, 40% of the total energy consumption of the entire European Union derives from the building sector and half of this consumption is used for heating, ventilation and air conditioning (HVAC) systems [1–3]. While the reduction of GHG emissions in new buildings has already been regulated by the European Union [3] i.e. all new buildings must be nearly zero-energy (NZEB) by the end of 2020 and all new public buildings must be NZEB by the end of 2018 energy saving and GHG emission reduction in existing buildings is still an open research challenge. In fact, within the EU Energy Efficiency Plan 2011 [4], the European Union planned to refurbish only around 3% (by floor area) of the existing buildings per year, implying a renovation of the whole building stock in over 30 years. This regulation, as well as the high economic cost that would have to be faced to renovate existing buildings, opened research opportunities. Indeed, in last decades, researchers and practitioners primarily focused on the improvement of the Building Energy Management Systems (BEMS). For instance, the widespread use of efficient BEMS has been estimated that may save only up to the 8% of the total energy consumption in the entire EU [1]. In particular, all around the world researchers started to investigate ways to automatize the HVAC systems in buildings, exploiting various types of algorithms and approaches such as the Model Predictive Control (MPC). MPC was widely used since the 1980s in the industrial sector, in chemical plants and oil refineries. The state-of-the-art for BEMS is based on predictive models able to forecast the energy consumption and to optimize it taking into account a few constraints (e.g. energy consumption, indoor comfort) starting from several input variables such as the outdoor temperature, the occupancy, the electricity prices and so on. A typical constraint is the comfort of occupants [5] . Various methods and algorithms have been studied: Stochastic Model Predictive Control (SMPC) [6], Artificial Neural Network (ANN) [7] or Multiagent System [8]. Generally, predictive algorithms were based on weather prediction [9] or occupancy data [10], considering the energy saving challenge only from a technical point of view. Despite the great effort in reducing energy consumption in existing buildings, in literature, there is still a lack of investigations which tackle the energy challenge from a different point of view, i.e. considering buildings as socio-technical systems, and which focus on users' engagement, on user behavioural change for energy saving [11] and on predictive adaptive comfort in real-time. The majority of researches focused on office buildings or on ad-hoc surveys [12] or on simulations [13] . For instance, Kimetal. [12] tested a Personal Comfort Model to predict indoor comfort of 38 occupants in an office building, while Carreira et al. [13] prototyped a mobile device solution and tested and evaluated it through simulation. In this paper we present the results of the ComfortSense research project based on an innovative methodology which exploited the potentiality of the Mobile CrowdSensing and the Living Lab approach to predict users' behaviour and indoor comfort through a predictive algorithm. The focus of Comfortsense (crowdSENSing for a sustainable COMFORT) was the decoupling of building energy consumption from the indoor thermal comfort of their occupants. In other words, the aim of the project was, first, to create a fruitful dialogue and interaction among people, the buildings and the energy management in order to increase the level of users' comfort while reducing the energy consumption and, second, to test and validate a robust predictive algorithm, i.e. the Direct Virtual Sensor, able to predict users' indoor comfort from the measurement of the indoor temperature, the relative humidity and the concentration of CO_2. By adopting a multidisciplinary approach and leveraging Internet of Data and Internet of Things technologies, as well as exploiting a Living Lab approach, with the ComfortSense project we developed and tested an innovative approach, taking into account both technical components (i.e. the buildings itself, the HVAC system, as well as sensors and the IT infrastructure) and the social components (i.e. the users, the energy management and the technical staffs) to engage users' for the energy management of large public buildings. We approached to the energy saving challenge, for existing buildings, considering it not only from a technical point of view but we considered that people and "places" interact constantly, affecting each others and consequently the energy consumption. For this reasons, we developed an IT infrastructure composed by (i) a Mobile App for Smartphones, (ii) a Wireless Sensor Network (WSN) (fixed and wearable sensors), (iii) an online dashboard and (iv) a few predictive algorithms, i.e. the Direct Virtual Sensors (DVSs) in order to exploit the huge potential of the Mobile Crowd Sensing (MCS) approach [14] ; subsequently, we tested it during a Living Lab of several months in order to engage buildings' users in the most natural way into an "aware" energy management. Finally, we exploited a robust predictive algorithm, the Direct Virtual Sensor, trained during the Living Lab from users' indoor comfort feedback in order to automatically manage the HVAC system of a building exploiting a collective intelligence. Exploiting the smartness of the collective intelligence, as defined by Surowiecki [15], i.e. the crowd is smarter than any single member of a group, we improved and generalized the existing adaptive comfort approaches. During the project, a thousand occupants (students, researchers, academic and technical staffs) in three buildings of the University of Turin were engaged to participate in a Living Lab [16] to co-design the IT solution and to test it for six months, in order to stimulate a behavioural change process towards a reduction in energy consumption. In particular, our contributions are the following: (1) we describe a technological solution for the management of a sociotechnical system by allowing interactions among users, the buildings itself and the energy management (2) we show that our Direct Virtual Sensor can achieve a satisfactory performance in predicting users' feedback, especially for extreme values, and it can help in simulating users avoiding time-consuming users' engagement campaigns (3) we show how user comfort can be improved, at the same time reducing energy consumption, (4) we discuss our experience with the living lab methodology and user engagement, providing suggestions for future researchers. This paper is structured as follows. In Section 2 we describe the current academic literature framework, introducing the concept of Indoor Adaptive Comfort, the research challenge on the decoupling of energy consumption from indoor thermal comfort, the Mobile Crowd Sensing approach and the Living Lab methodology. In Section 3 we describe in detail how we exploited the Living Lab methodology to co-design and assess our solution, the Mobile App interface as well as the crowdsensing surveys we adopted. In Section 4 we present the project results in terms of IT infrastructure (WSN and wearable device, MCS and Mobile App, DVS and forecasting), users engaged and surveys on thermal comfort. Moreover, we discuss key takeaways, opportunities and difficulties encountered as well as some best practices to adopt. Finally, in Section 5 , we frame the results of the project in terms of users engagement and adaptive indoor comfort, giving some suggestions on further improvements.

2. Background

2.1. Indoor comfort

In the literature, indoor environmental comfort of occupants has been widely studied for decades. In the ’70s, the so-called rational approach focused on developing thermal comfort indices such as the Fanger’s Predictive Mean Vote (PMV) [17] which summarizes the occupants comfort on a scale from −3 to +3 where −3 is cold, 0 is neutral and +3 is hot and the range from -1 to +1 represents the optimal thermal comfort. The PMV revealed several complexities and difficulties in measuring a few specific variables (e.g. metabolic rate, clothing insulation) in real daily life conditions. In fact, in later years, several studies like those by Nicol and Humpreys [18] , demonstrated that occupants declared a wider thermal comfort range than Fanger’s results. For decades, re-searchers investigated correlations, interdependencies and relation-ships among indoor occupant thermal comfort and outdoor temperature [19] , indoor temperature and humidity [20] , the impact of different seasons and climate zones [21] . Moreover, various re-search studies and field surveys demonstrated how the spreading of HVAC systems decoupled user thermal comfort from outdoor temperature [22]. In fact, the occupant thermal comfort tempera-ture range is almost constant with respect to outdoor temperature within buildings with HVAC systems while, in naturally ventilated buildings, occupant thermal comfort increases as outdoor temperature raises and the opportunity to reduce cooling energy demands by designing natural or hybrid ventilated buildings was highlighted [23] . In fact, Humphreys and Nicol [22] showed how within natu-rally ventilated buildings indoor comfort and the comfort temperature (T_c) is directly proportional to the outdoor temperature (T_o) and follows approximately the relation $T_c = 13.5 + 0.54 T_o$. Consequently, during the ’90s and the first decade of the new century the new concept of Adaptive Thermal Comfort emerged [24] . The fundamental principle of Adaptive Thermal Comfort states “If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort” [25] . By assuming this principle, the relationship between user thermal comfort and the surrounding environment was investigated demonstrating that thermal comfort depends on the context and on the interactions between occupants and buildings [26]. For instance, Leaman and Bordass have revealed that occupants tend to “forgive” more if they have more control on the building itself [27].

2.2. Crowdsensing

In recent years, a new approach has emerged, based on participatory sensing [28] and on Wireless Sensor Networks. Crowdsensing is an emergent applied research field which exploits human and machine intelligence in order to collect data from a “crowd” of target citizens. Surowiecki [15] argued that a crowd may often take better decisions than any single group member. Suriowiecki, as well as Malone et al. [29] with their definition of collective intelligence, identified four key qualities for crowd smartness: diversity in opinion, independence of thinking, decentralization and opinion aggregation. More recently a variant of Crowdsensing, the MCS approach, has been adopted in many research projects, mixing data gathered from mobile apps and data from mobile social networks. Bin Guo et al. [14] defined four key features for a well-designed MCS approach: (i) Citizen Participation (Explicit or Implicit), (ii) User Motivation, (iii) cleaning low quality data (e.g. fake profiles, wrong feedbacks, . . .) and (iv) data mining. In the field of behavioural change for energy efficiency, the first two aspects be-come crucial. Crowdsensing, indeed, can gather data both engaging users (explicit) and without an action from the users (implicit), and an MCS approach has to be designed taking into account the degree of user involvement in the sensing process. With respect to User Motivation, instead, in order to engage a large number of users, a gamification process has to be exploited promising financial monetary gain, interest or entertainment, as well as promoting social and ethical reasons. Finally, with respect to the last two features, a human-machine, human-building interaction has to be structured around a tradeoff between user control and system automation [30] , as in the work of Kamar et al. where probabilistic models were used to predict the behavior of workers during an online crowdsourcing process [31] .

2.3. Behavioural change

In recent years, crowdsensing for behavioural change has be-come a growing research field, which is however still largely un-explored. Morganti et al. [32] categorized behavioural change re-searches related to energy into three main areas: (i) environmental education; (ii) consumption awareness and (iii) pro-environmental behaviour (PEB). Different strategies have been applied for energy efficiency in buildings, from structural interventions [33] , such as the upgrade of technological infrastructure, to monitoring feed-back and psychological strategies [34] . A best practice consists in combining technological and psychological approaches [35] . Steg and Vlek’s [36] behavioural theory, for instance, identified four best practices to develop a PEB strategy: specific behaviour, analysis of involved factors, type of intervention and evaluation of its efficacy. Osbaldiston and Schott [34] , instead, defined four types of interventions to engage occupants for energy efficiency: structural interventions to upgrade technological infrastructures, informational strategies to increase user awareness, feedback to gather real-time users' perception and social approaches to show "what others do" [37] . As explained in the previous paragraph, the best practice is to mix different strategies taking into account that, for user behavioural change, "knowing what to do" is not as effective as "knowing how to do" [38] . On top of that, according to Chatterton [39] , behavioural change can be studied through different perspectives: (i) economical, where cost-benefit calculation and rationality play a crucial role; (ii) psychological, where individual factors are prominent; (iii) sociological, where other variables, such as social, environmental and structural ones, can be taken into account; (iv) educational, where the focus is towards the learning experience. It is useful to consider different key aspects, mixing both individual and structural features. Since effort s towards behavioural change should take into account not only in-dividual characteristics but also structural features, it is fruitful to focus on the Triandis model [40] , where a crucial role is played by intention, which includes individual and social aspects, as well as habits which are strictly connected to daily routine and routinized behaviour. Finally, Triandis put facilitating condition in his model, highlighting that other features, such as organizational constraints, may affect users' behaviour. Over the years, the behavior change issue in energy domain has been tackled also from a technological perspective, designing systems explicitly aimed at affecting the individual energy consumption [41–44].

2.4. Living Lab

In the late '90s, Living Labs (LLs) emerged as a new approach to engage citizens and stakeholders within research projects and innovation processes in order to design and test innovative technologies [45] . The main aim of Living Labs was to validate new technologies in real situations and environments, avoiding tests in a controlled environment such as a laboratory. In recent years, the Living Lab approach quickly spread within Higher Education Institutions and it is currently widely exploited worldwide for research projects. LL is a very general approach and it may be adopted and applied to any research field [46] ; the original idea emerged from the concept of "Every-day Computing" [47] and the "House of the Future", a high-tech house where users, in an immersive environment, could test new technologies in an innovative way [45] . Since the early 20 0 0s, various applied research projects explored the op-opportunities for the LL approach. For instance, the University of Colorado built an "Adaptative House", i.e. an innovative house able to forecast water usage, the user lighting preferences as well as user occupancy [48] ; an interactive office was developed at the Massachusetts Institute of Technology in order to analyze the natural interaction of users during their everyday life thanks to sensors, cameras and microphones [49] . Orr and Abowd, instead, created an Aware House at the Georgia Tech Living Labs, to analyze the human-machine interactions [47] . In the past 20 years, LL was defined as a methodology [50] , an environment [51] as well as a system [52] . Depending on the point of view the focus changes: from the environment point of view, the focus should be on user communities and IT infrastructure, from the methodology side, LL should highlight user engagement, while, from the system perspective, the aim should be analyzing, at the same time, the environment-users-objects interaction. From the definition "house of the future", LL definition evolved and, nowadays, it is rather associated with the co-design process of new technologies. For instance, within the Corelabs Report, Living Labs Roadmap 2007–2010, 5 key principles were identified [52] : (1) "continuity", to plan a long-term LL; (2) "openness", to focus on the open engagement process; (3) "realism", to reproduce real-world environment; (4) "empowerment of users", to actively engage users; and (5) "spontaneity", to reproduce everyday life situations in a way that does not affect user perception. On top of previous studies, in recent years, the European Commission defined the Living Lab as a *"user-driven open innovation ecosystem based on a business citizens government partnership which enables users to take an active part in the research and in the innovation process"*[16] , highlighting the three fundamental aspects: (1) "the users" are involved in the design process to better discover emerging user behaviours; (2) "the partnerships" all relevant players and stakeholders are engaged thanks to partnerships among businesses, citizens, and local authorities, bridging the innovation gap between technology development and the user adoption of new products and services; and (3) "the research, development and innovation" for early assessment of the socio-economic implications of new technological solutions by demonstrating the validity of innovative services and business models.

3. Methodology

ComfortSense exploits the Living Lab approach (see Section 3.2) to involve all actors and stakeholders in an experimentation phase where the IT tools, technologies and comfort variables are codesigned and tested. The following tools and technologies are used to collect comfort-related data and foster behavioural change (see Section 3.1): (a) a Mobile App, to communicate the comfort perception and to engage occupants; (b) a Wireless Sensor Network composed of fixed sensors (temperature, humidity and CO_2 concentration), iBeacons, an occupancy sensor and wearable devices, and (c) a Direct Virtual Sensor, namely an algorithm able to predict the level of comfort of the occupants based on the real-time values of temperature, humidity and CO_2 , even in the absence of real-time feedback. The IT infrastructure and the flow of gathered data is described in Fig. 1 . The core of the infrastructure, the data gathering layer, was based on the WSN, used to collect the "objective" variables, and the Mobile App, exploited to gather the "subjective" data from users. All data were stored into a central repository (data storage level) and then used to feed the Direct Virtual Sensors (simulation layer). Afterward, the forecasting of the Direct Virtual Sensors (see Section 3.3) as well as the energy cost prediction from dynamic energy simulation (see Section 3.4 , optimization layer), together with user feedback and real time objective variables were exploited to develop an online Dashboard for the Energy Management of the University of Turin and the Mobile App interface for behavioural change (data visualization layer). Finally, energy and comfort forecasting were used to develop strategic decision support tool for energy management (decision support layer). The design process, as well as the selection of suitable rooms for sensor installation in the pilot buildings (see Section 3.6), were guided by use-case scenarios that involve users, spaces and the energy management (see Section 3.5).

3.1. Behavioural change

Following Chatterton [39] , we assumed that users' beliefs and attitudes, added to external input such as communication campaigns or educational programs, were not enough to improve users' behaviour related to energy consumption reduction in public buildings. In fact, buildings need to be redesigned in order to put users in condition to save energy by adopting more sustainable practices [53] . This is one of the reasons why ComfortSense aimed to act on both users' awareness and technical aspects. In our approach, behavioural change was expected to occur due to the fostering of users' actions within the socio-technical system. In other words, enhancing users' capability to interact with the building should be the key to let them behave in more sustainable ways, during the project and after its end. People and places interact in everyday life, influencing the amount of energy required and consumed. Consumption takes place inside a socio-technical system, which implicates that in order to enable an energy efficiency process through behavioural change all the components of the system need to be taken into account. There are two macro components in the system, one technical and one social. The first one gathers the whole HVAC system (which involves infrastructure, energy flows, existing sensors...), the architectural features of the buildings, the existing technology (e.g. computers, coffee machines...). The social component, instead, refers to people with their behaviours, competences, comfort perception, environmental and energy awareness, habits, their relations with places and spaces and so on. Working exclusively on one component or one aspect of the macro component means excluding other relevant factors that could highly influence the whole process. In this sense, ComfortSense aimed to improve the socio-technical system as a whole, enhancing the information and communication flows among the ecosystem and enabling a behavioural change of the system toward a more sustainable management. As Fig. 2 points out, behavioural change is a complex process. Not only it consists in acquiring more information, but it also makes the information comprehensible, acceptable and adaptable in modified behaviours and perceptions. Currently, people acting in and using public buildings are far from being aware of the energy flows and consumption of the buildings in which they are working or temporarily living. They are even less aware of the impact that the required comfort levels have on the energy system and, secondarily, on the environment. Our idea was to leverage precisely the comfort dimension in order to make the energy consumption more comprehensible and to enable a comfort request that is adaptive on the specific context instead of standardized on global levels. Obviously, behaviours carried out by people in collective buildings are substantially different from those that take place in the domestic environment, but nevertheless highly significant. Our challenge was to work on this peculiar set of behaviours, in order to develop solutions that can be useful to solve the energy consumption problem in those environments both public or private where a large number of occupants is involved.

3.2. Living lab & codesign process

The LL phase was planned in order to involve the users of the buildings (students) in the innovation process which took place in two different stages. In practice, in the first stage, nearly 40 students from the Communication, ICT and Media master's degree course were asked to participate in a laboratory whose aim was to let them work on pilot ideas to manage indoor comfort in a sustainable way. The participants were asked to provide solutions working in groups with very strict timing and rules. Such an activity was conducted using the design studio methodology from user experience and user interface design fields. Participants were divided in small groups (5–6 each) and each group had to address at least one design challenge. A design challenge is formulated as a sentence beginning with "How might we... "and was intended as a main problem to be solved with reference to energy sustainability. Then, each participant, in each group, had to suggest individually new solutions for addressing the design challenge individuated. Finally, the group, once selected the most promising solution, had to present it to all the other participants. Although some of the proposed ideas were not strictly related to HVAC energy consumption (since their assignment just mentioned some general concepts of comfort and consumption), part of the output laid the foundations for the development of the smartphone app's interface and main functions. During the Living Lab design phase, participants designed six comfort variables on a 1–5 point scale and on a binary scale (0–1): (i) global (1–5); (ii) thermal (1–5); (iii) humidity (1–5); (iv) brightness (1–5); (v) noise (1–5) and (vi) air quality (0–1). More precisely, for global and noise comfort, discomfort was expressed with a vote of 1, normal condition with a value of 3 and the optimal comfort with 5. On the contrary, for thermal, humidity and brightness comfort, due to the symmetry of discomfort condition, the optimal condition was expressed with a value of 3, while the discomfort both with a value of 1 (e.g. too dark/too cold) and of 5 (too bright/too hot). Finally for the air quality index, a value of 0 represented a good air quality while 1 an high CO_2 concentration. In the second stage, in the months following the design phase, students were asked to contribute to data collection providing feedback on their perception of comfort using the same app they contributed to design. During this phase, students were involved and asked for their feedback during their daily routine in order to collect as many comfort data as possible.

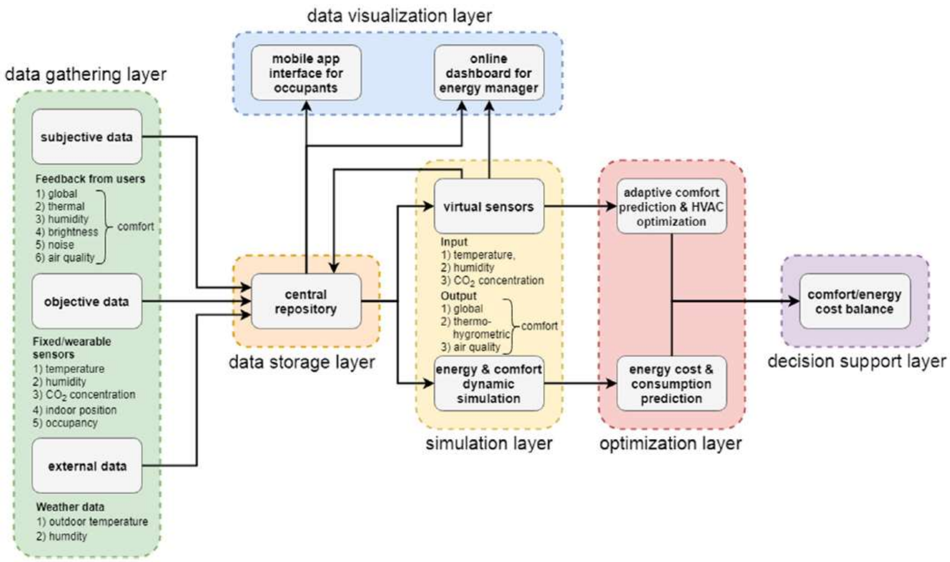


Fig. 1. IT infrastructure and data flows.

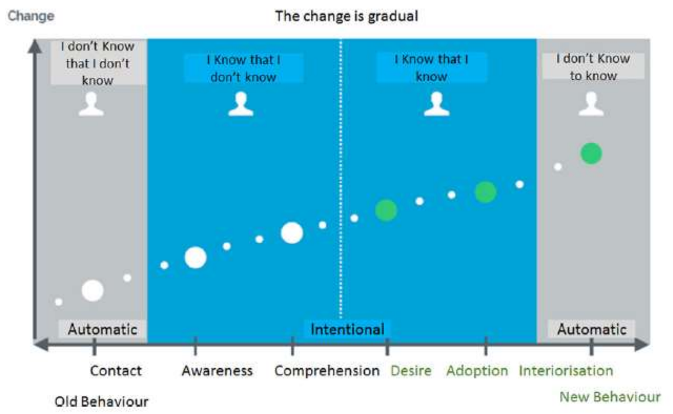


Fig. 2. A three steps - i.e. automatic–intentional–automatic - behavioural change process: from a "I don't know that I don't know" state to "I don't know that I know" state.

3.3. Crowdsensing & direct virtual sensing

The crowdsensing approach aimed to collect a large amount of users' comfort feedback during a brief period from few weeks up to a few months in order to feed and train the predictive algorithms for the Direct Virtual Sensors. The difference from few weeks up to few months was due to the lectures schedule and to the constraints on the project timeline. In fact, the crowdsensing approach was used to test an innovative approach, named Direct Virtual Sensing [54,55] , and to develop a few Direct Virtual Sensors able to predict and simulate users' comfort feedback starting from environmental absolute variables (e.g. temperature, relative humidity, CO_2 concentration). For this purpose, users' feedback were intensively collected during a short period for each equipped space and the collected data were used to initially train the predictive algorithm of the three developed Direct Virtual Sensors. In particular, the three developed DVSs were used to predict: (1) the global, (2) the thermo-hygrometric and (3) the air quality comfort. Each DVS was designed to predict future users' feedback from a few environmental objective measurements as described by the following equation, $y(t+1) = f$ _$u(t)$ _where $y(t+1)$ is the output (i.e. the comfort feedback) at time t+1, f is a non-linear function and $u(t)$ is the array of the average values of the environmental variables (input) at time t. More precisely, each DVS needs the following variables as input: (1) temperature, relative humidity and CO_2 (global comfort), (2) temperature and relative humidity (thermo-hygrometric comfort), and (3) temperature, humidity and CO_2 (air quality comfort). Thus, for instance, the general comfort DVS equation is described by $y(t+1) = f(u1(t), u2(t), u3(t))$ where $u\ i$ represents the average value of temperature ($u1$), relative humidity ($u2$) and CO_2 concentration ($u3$) at time t.

3.4. Dynamic energy and comfort simulation

We used the simulation software IDA Indoor Climate and Energy (EQUA Simulation AB) 2 , which allows to dynamically simulate the user thermal comfort, the indoor air quality as well as the energy consumption of the pilot buildings, to simulate various user behaviour scenarios and their related impact on energy consumption in comparison to a reference scenario (scenario 0). The scenario 0 was tuned according to the actual energy consumption of one of the pilot buildings, i.e. the Campus Luigi Einaudi. The aim of simulating user behaviour scenarios was to quantify the change of the energy consumption for various occupant behaviours. Three types of user were analysed: 1) the "Standard"user, 2) the "Aware"user and, 3) the "Unaware"user. In order to model the buildings and the user behaviour as close to the reality as possible, gathered data from the Living Lab were used to calibrate the three scenarios. In particular, we designed the "Standard"user scenario according to the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) Standard, as well as the Italian and European regulations i.e. UNI EN ISO 7726 (1995–2002) [56] , UNI EN ISO 7730 (2005) [57] , ASHRAE Standard 55 [58] . The "Aware"and "Unaware"user scenarios, instead, were modeled by varying, starting from the "Standard"scenario, five environmental parameters which affect the user perception related to indoor comfort. As defined by the Italian regulation and by the ASHRAE Standard 55, the reference for the thermo-hygrometric comfort are the *PMV* (Predicted Mean Vote) and the *PPD* (Predicted Percentage Insatisfied) indices. We adopted the Italian regulation UNI-EN 7730 limit for a comfortable indoor space which means a *PMV* ±0.5 and a *PPD* < 10%. It is noteworthy that the Italian limit is much stricter than the ASHRAE Standard 55 recommendations (*PMV* ±0.85 and *PPD* < 20%). In terms of indoor air quality, instead, we adopted the ASHRAE Standard 62 [59] where an "acceptable"indoor air quality is defined when at least 80% of occupants doesn't express dissatisfaction, and according to the EN 15251 [60] where the limit of CO_2 concentration for indoor space is defined. Finally, in terms of visual comfort we referred to the Italian regulation (UNI EN 15251). The comparison between scenarios was made with respect to the Hourly Performance Index [61] (PI) which measures the hourly cumulative distribution of satisfaction (e.g. a PI = 1 implies that all occupants are always satisfied). Finally, weather conditions and related outdoor environmental variables are based on the ASHRAE dataset for the City of Turin.

3.5. Description of the scenarios

In a socio-technical system, such as a university building, users are related to the spaces through the activities occurring inside it. Space may be a classroom, a library, an office, a laboratory, the great hall. Activities depend on the calendar of lessons, weather forecasts, historical data on participation in the courses, historical data on attendance at lessons in current courses, special planned events. Thus, content, environmental information and data derive from space characteristic, from users and from their daily interactions. For an optimal management of a socio-technical system, in each context and situation the Energy Manager should have access to all available data historical and real time data as well as forecasts in order to take the best decision to optimize users' comfort, energy consumption and HVAC system maintenance. For each type of space within a university and for each type of possible users' activity, we create proper scenarios in order to envision possible interactions between users, spaces and the energy management and to forecast conceivable users' reactions. We present here various scenarios within three different spaces: a classroom, an office, a library. The "Classroom"scenario is based on the typical activity of a student going to lesson. Let's assume that a student, Gina, is still at home. Thanks to the app, she can check detailed information about the temperature within the classroom, the number of expected people and she can get tips on the proper clothes to wear in order to balance comfort and energy saving. Meanwhile, the Energy Manager sets the optimal light and temperature based on classroom occupancy forecast. The student Gina, during the path from home to the university, brings with her a wearable device which measures outdoor temperature and Gina's activity (e.g. an accelerometer registers the rapidity of movements). The ComfortSense sensors network starts to measure the situation within the classroom (like the number of people, temperature and humidity) and asks present students to provide feedback on their comfort perception, sending all gathered information, in aggregated form, to the Energy Manager. Meanwhile, unfortunately, Gina is running, due to a bus driver strike, to arrive on time at the lecture. When she arrives in the classroom, she feels hot and decides to send a negative feedback. The ComfortSense App recorded a very cold outdoor temperature and the recent strenuous activity of Gina and, consequently, the ComfortSense system decides to refuse Gina's feedback. After a while, Gina sends another feedback, better than the first one but still complaining about thermal discomfort. In this second case, the system accepts Gina's feedback. Thus, the Energy Manager receives the negative feedback and, due to other negative feedback previously received, plans to reduce the temperature by 1 $°C$, increasing the comfort and reducing the energy consumption. Finally, Gina, after the lecture, consults her Mobile App, where an explanation about the refused feedback is provided, together with a comparison between her comfort level and those of the other users. Thanks to this information Gina learns to wait 10–15 min and cool down before expressing a comfort feedback in the classroom. The "Office"scenario simulates a worker going to his office. Luca is going to work in his office, where two of his colleagues are working since the morning. All three office workers send information about their state of comfort through ComfortSense App. Since Luca has been the last to arrive at the office, his perception of comfort can be different from the others. The system will use Luca's feedback both to send information to the Energy Manager and to understand Luca's preferences. The system adjusts according to Luca's and his colleagues' preferences. The "Library"scenario involves an employee who works there every day, and a few students, who are going to study in the library. Luisa perceives a higher temperature than the previous week, probably because a lot of students reported a discomfort feedback in the past weeks. The system knows that Luisa is working in the library all day long and every day; thus, her feedback is weighted slightly more than students' feedback.

(a) Plug and play Fixed Sensor to monitor temperature, relative humidity and CO_2 concentration

(b) Meshlium Xtreme Access Point to monitor indoor occupancy based on Wifi and bluetooth active devices.

Fig. 3. Adopted hardware technologies: (a) fixed sensor on the left and (b) Meshlium Xtreme on the right side.

3.6. Description of the spaces

Starting from these scenarios, we carried out the pilot test for ComfortSense within three buildings of the University of Turin: Campus Luigi Einaudi, the Physics Department and the School of Management and Economics. We implemented the Wireless Sensor Network in classrooms, libraries, offices as well as IT laboratories. Classrooms and offices, involved in the pilot test, were equipped with fixed sensors and were located in different parts and floors of the pilot buildings. The fixed sensors were fixed directly to the wall of the equipped spaces; in particular, each sensor was installed at an height of more or less 1,5 m and not exposed to direct sunlight. The wearable devices, moreover, allowed users to interact in all common spaces (e.g. corridors, halls, stairs, ...) and other classrooms without fixed sensors. Campus Luigi Einaudi is the largest structure of the University of Turin, with more than 45, 0 0 0 m^2 and 14, 0 0 0 m^2 of green, 5 libraries (10, 0 0 0 m^2) and 70 classrooms. The total number of users, including both students and employees, counts more than 10,0 0 0 people. We set up sensors in various spaces: the main library, which is distributed on four floors for a total of 10, 0 0 0 m^2 , a computer lab with 120 seats, a study room with 60 seats, a normal classroom of about 100 seats and 3 administrative staffoffices. The Physics Department is a historical building from the early 1900, although partially rebuilt in the early 1950s, with a newer part built in the ’70s. The Physics Department covers about 170 0 0 m^2 for a total volume of 65411 m^3 . Representative spaces analyzed in Physics Department were: the Aula Magna with 150 seats, a computer room with 57 seats, an average classroom, with 60–70 seats, the library study room with 30–40 seats and a small classroom with 20–30 places. The School of Management and Economics is divided between an older part, built in 1889, and a new one, inaugurated in 2009. This complex architectural structure uses 22, 600 m^2 , provides about 50 0 0 seats in the 38 classrooms for about 10,0 0 0 students. Representative spaces selected from this structure were: 3 classrooms, respectively containing 20, 10 0, 40 0 seats, a computer room, an office with five workers and a study room with a maximum capacity of forty students.

4. Results and discussion

4.1. IT infrastructure

A CE certified plug and play fixed environmental sensor (shown in Fig. 3 a) was developed during the ComfortSense project. The designed sensor was based on the Intel Edison computer-onmodule developed by the Intel. The Intel Edison was a computeron-module with high performance i.e. Atom 2-Core (Silvermont) @ 500 MHz, LPDDR3 1 GB, 4 GB EMMC and various signals as Bluetooth low energy 4.0, 2.4 and 5.0 GHz Wifi, USB, GPIOs, SPI, I 2 C, PWM, etc. and small dimension −25 mm ×35.5 mm. The sensor was developed to measure CO_2 concentration, thanks to the COZIR sensor (Gas Sensing Solution), and temperature and relative humidity, thanks to the SHT21 (Sensirion). Moreover, the fixed sensor was developed with a web server onboard to setup and to easily visualize the gathered measures on temperature, humidity and CO_2; finally, the gathered environmental data were sent, through 5.0 GHz Wifi, in near-real time i.e. every 5 min to the central repository. In the Study Room, a Libelium Meshlium Xtreme (shown in Fig. 3 b) was installed; the Meshlium Xtreme is an IOT gateway to connect any sensor to any cloud platform (more than 45 cloud platforms) through various types of communication (RF, 4G, Wifi, Ethernet). In particular within our project, the Meshlium Xtreme was used to monitor the occupancy i.e. number of people within the Study Room; in fact, the Meshlium Xtreme allows to detect iPhone and Android devices, and, in general, any device with Wifior Bluetooth interfaces. Devices, in order to be detected, do not need to install any mobile app, as well as they do not need to be connected to a specific access point. In fact, every device, automatically, sends a “hello!”message communicating its presence. In this way, the Meshlium Xtreme is able to monitor very precise information about the number of people, type of device e.g. MAC address, the Class of Device (CoD), such as smartphone, laptop, LAN/network access point the strenght of the signal (RSSI) which allows to identify the average distance and other parameters. Moreover, an indoor geolocalization system was developed based on the iBeacon technology (shown in Fig. 4 a). Therefore, users could be geolocalized, thanks to the bluetooth LE 4.0 through the ComfortSense Mobile App on their smartphone, to the nearest indoor space (classrooms, offices, halls, ...). Offices, and tiny indoor spaces, were equipped only with one iBeacon, while large spaces, such as classrooms, halls and corridors, were equipped with two, or more, iBeacons, allowing a more precise geolocalization of users (e.g. on left-right side of the classroom, near the entrance door/close to the windows). Users’ engagement was improved thanks to the Wearable SensorTag device (shown in Fig. 4 b). The SensorTag is a wearable device, small enough to be used as a keychain or as necklace, able to measure in real-time indoor temperature, relative humidity as well as movement, thanks to an accelerometer. Within ComfortSense, Wearable SensorTags were given to all Living Lab participants to allow them to constantly measure and visualize the temperature and humidity in any indoor space of the pilot buildings directly on ComfortSense Mobile App, thanks to Bluetooth communication. Living Lab participants, thanks to the ComfortSense Mobile App were allowed to send temperature and humidity measurements to the central repository, self-declaring the classroom or the office, at any time. In such a way, we were able to collect data in any space within the pilot buildings without installing fixed sensors in all spaces, avoiding obviously high hardware and installation costs. Mobile App users registration allows to avoid redundant data. Finally, all the gathered data from fixed and wearable sensors (objective data), from the Mobile App (subjective data), occupancy and localization data, as well as data generated by the Direct Virtual Sensor, were collected in a central repository, a relational database based on MySql, as shown in Fig. 1 . Collected data were used both for an online web-based dashboard for the energy management and for the users within the Mobile App. More precisely, an online interactive dashboard was developed, according to the energy manager needs, in order to show specific (in space and time) user feedback in real-time, as well as daily, weekly or monthly average values related to objective and subjective measures.

(a) Bluetooth iBeacon to allow users indoor geolocalization.

(b) Wearable SensorTag to allow users to measure temperature and relative humidity in any space at any time.

Fig. 4. Adopted hardware technologies: (a) iBeacon on the left and (b) SensorTag on the right side.

4.2. Mobile App

A Mobile App for Android-based smartphones was developed starting from suggestions provided by Living Lab participants. The ComfortSense Mobile App aimed to engage users in a more aware energy management of the pilot buildings, to improve and boost behavioural change of occupants as well as to provide a userfriendly and immediate IT communication channel between occupants and the energy management. Our approach laid on, first of all, a user engagement process and, secondly, on a behavioural change step. The user engagement process was based on the use of two specific Mobile App functionalities. Users were encouraged, through an ad-hoc communication campaign, to: (1) communicate their comfort feedback i.e. general comfort and thermo-hygrometric, air quality, brightness and noise comfort and, (2) wear the SensorTag wearable (see Fig. 5) to collect temperature and relative humidity data. This ICT approach was designed in order to fill a common management gap for large public buildings, i.e. the lack of simple tools which allowed users to participate to the energy management of a public building. More precisely, geolocalized users' feedback (*data gathering layer*) were sent and stored in real-time to a central repository (*data storage layer*). All stored data were used to inform in real-time the energy management of particular comfort/discomfort condition thanks to an online dashboard, allowing a direct communication from users to the energy management. Moreover, the stored data were used to directly show to the users in real-time the environmental condition of a specific space thanks to a users interface integrated within the Mobile App (*data visualization layer*). Users were given the possibility to visualize, at any time and for any space within the pilot buildings, the indoor temperature, the relative humidity, the CO_2 concentration and other users' feedback. The Mobile App had no push up notification system so that the decision to visualize environmental conditions or other people's feedback within a specific space was left to users. The behavioural change process, instead, was based on the scheme presented in Section 3 . As shown in Fig. 2 , the modification of user habits had to conduct users from an automatic behaviour, through an intentional one, up to a new automatic behaviour; in particular, moving users from an "I don't know that I don't know"state to the "I don't know that I know"state. This process was meant to increase user awareness by providing precise information on, for instance, the impact of their actions. Users were able to visualize the thermohygrometric condition, the amount of lux (brightness) and decibel (noise), as well as the average of the comfort feedback. Moreover, once a user feedback for a certain room was sent, the Mobile App directly showed the average comfort for that room. In this way, users had the possibility to reflect on the relation between their own comfort perception, the real indoor temperature, and the level of comfort expressed by other users.

4.3. Direct virtual sensor

During the whole project (9 months), about 650 users were engaged for a period between 3 and 6 months, storing more than 50 0 0 feedback on Global Comfort (subjective variable). The period of test varied between 3 and 6 months due to the delayed implementation of the fixed sensors within a few of the equipped spaces and the variation in the occupancy schedules (e.g. lectures schedules, exam period, .). Moreover, about 50 0,0 0 0 temperature measurements, as well as humidity and CO_2 values, were stored (i.e. one measurement every five minute for each equipped space) into the central repository. More precisely, each fixed sensor was programmed to send temperature, humidity and CO_2 concentration measurements every five minutes to a central repository through 5.0 GHz WiFi, as described in Section 4.1 . As comfort feedback could not be acquired periodically (but only asynchronously depending on when users gave feedback), the sensor data and corresponding comfort (DVS input and outputs respectively) were not-consecutive data samples in the time. The input/output pairs were averaged over a period of 5 min. Approximately 70% of the available input/output data pairs were used for the DVS training, while the remaining 30% of the data was used for validation. This breakdown was divided equally between the different periods of the year. Two methods were used to train and implement the DVS in order to set membership [55] and sparse approach [62] . Sparse algorithm consists in approximating a function using a "few" basis functions properly selected within a "large"set. More precisely, a sparse approximation is a linear combination of "many" basis functions, but the vector of linear combination coefficients is "sparse", i.e. it has only a "few" non-zero elements. Deriving a sparse approximation of an unknown function from a set of its values (possibly corrupted by noise) is here called sparse identification. In Set-membership approach, estimation noise is supposed to be unknown but bounded, i.e. the only knowledge about noise consists in its bounds evaluated in a given norm (deterministic and not statistical). A set of all admissible solutions is found. In this case, such a set contains all the feasible solutions of the problem, thus providing an evaluation of the uncertainty associated to the estimation problem. The sparse algorithm without autoregressive component was used to implement the DVS. Fig. 6 , on the left side, shows results during the validation process for the Global Comfort DVS related to one of the equipped and monitored spaces during the research project, the Study Room at Campus Luigi Einaudi. The red line represents the real users' feedback $y_{user}(t)$, while the blue line exhibits the trend of the predicted value (i.e. the output of the DVS) $y_{DVS}(t)$. One can notice how the DVS algorithm properly forecasts extreme comfort values (value 1 = high discomfort; 5 = high comfort), while for high-volatile user feedback (i.e. when different users, at the same time, express high comfort and high discomfort) the DVS algorithm tends to average the results and consequently fails to predict user behaviour. More in detail, Fig. 6 , on the right side, shows the probability density function (pdf) of the prediction error, $y_{DVS}(t) - y_{user}(t)$: the pdf shows that, on average, 75% of the user feedback $y_{user}(t)$ falls on the range of $y_{DVS}(t) \pm 0.5$ and the 95% of the users' feedback lies in the range $y_{DVS}(t) \pm 1$. Finally, we report the results for the other two DVSs within the same space, the Study Room. The thermal-hygrometric DVS, tested on the same user feedback dataset, showed a slighty larger error with respect to the Global Comfort DVS (±0.5 for the 65% of the feedback and ±1 for the 80%), while the air quality DVS was much more precise (97% of the feedback were perfectly predicted). The same robustness test was conducted for every designed DVS and every equipped space, achieving similar prediction results.

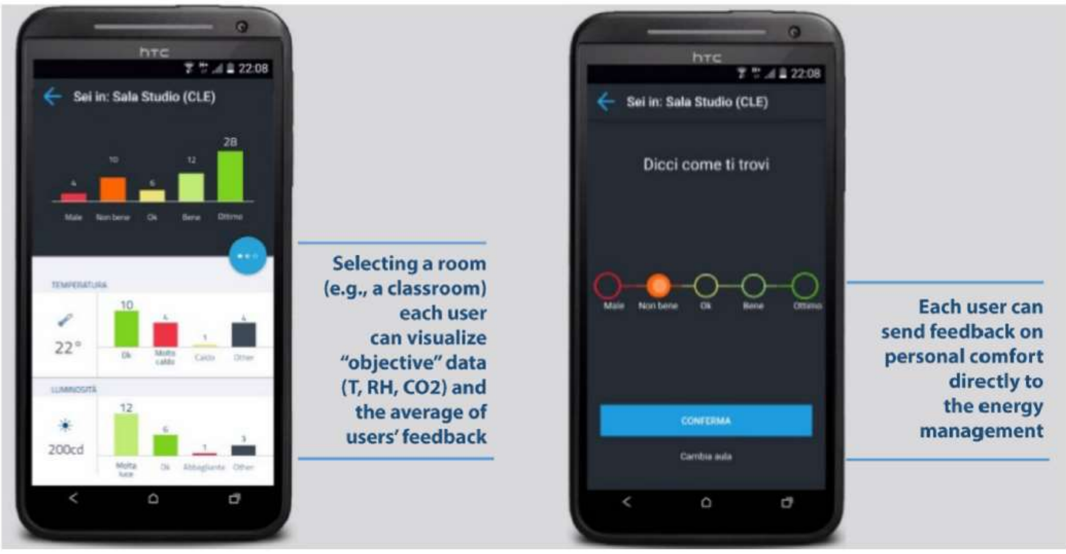


Fig. 5. Screenshot from the Android Mobile App. (a) On the left side, the visualization on average comfort of other users, and (b) on the right side, the function which allows users to send feedback to the energy management.

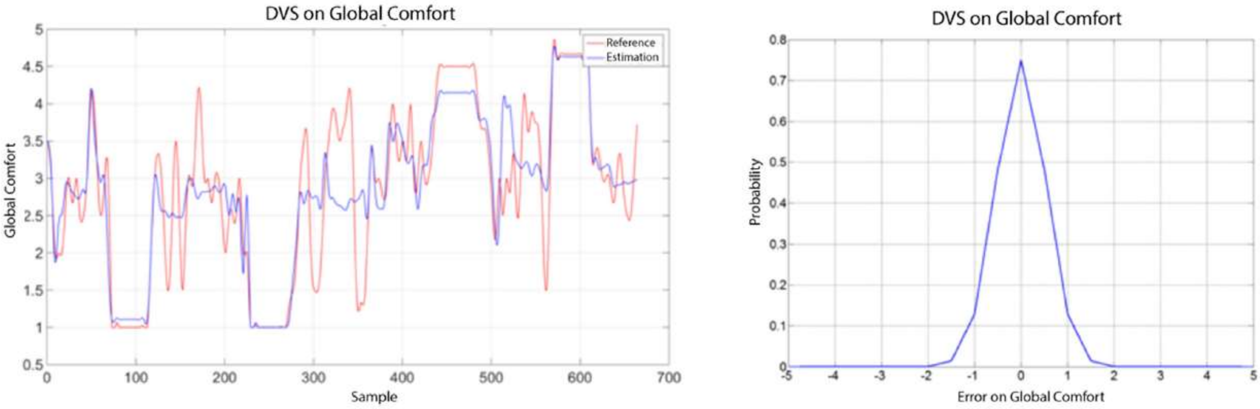


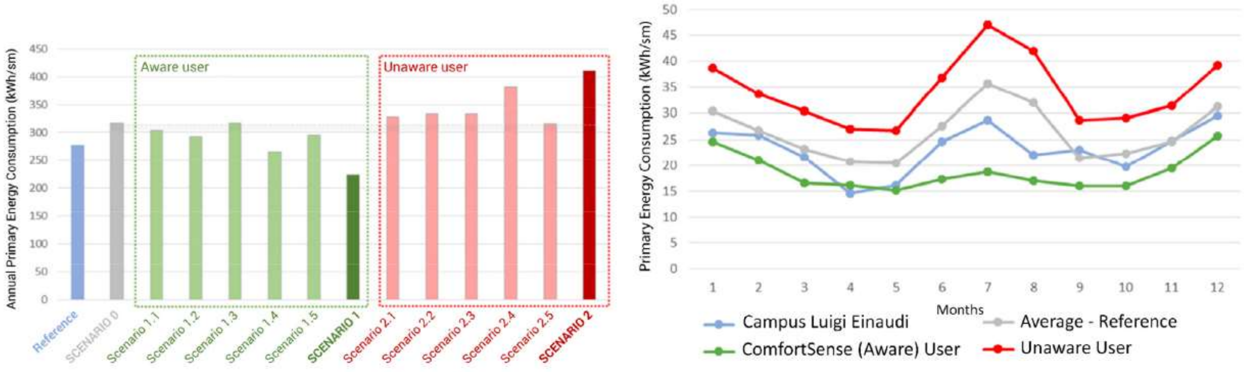
Fig. 6. Global Comfort DVS. On the left side red line shows real users' feedback, while blue line the algorithm prediction; on the right side is the probability distribution of the distance between the predicted feedback $y_{DVS}(t)$ and the real feedback $y_{user}(t)$ (i.e. x-axis represents $y_{DVS}(t) - y_{user}(t)$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.4. Energy and comfort simulation

As described in Section 3.4 , three scenarios for the energy simulation were defined the "Standard"user (reference scenario scenario 0), the "aware"user (scenario 1) and the "unaware"user (scenario 2) based on five variables: 1) summer temperature setpoint ($°C$), 2) winter temperature set-point ($°C$), 3) relative humidity (%), 4) brightness (lux) and 5) CO_2 concentration (ppm). More precisely, we referred to the European Standard EN 15251 [60] and to the PMV index [57] in order to set constraints and boundaries for the simulated scenarios. With respect to the EN 7730, a value of −0.16, −0.24 and −0.11 was obtained, respectively for the Reference scenario, the Aware scenario and the Unaware scenario, for the PMV index during the winter period, while for the summer period we achieved, respectively, a value of 0.02, 0.08 and 0. Further details on simulation are provide in Fabi et al. [63] . The three main scenarios are summarized in Table 1 where the limit on the temperature, the relative humidity, illuminance and CO_2 concentration set points are shown. First, starting from the reference scenario 0, modeled according to the annual energy consumption of the building, each single variable, one-by-one, was modified to simulate the energy consumption of the building, by maintaining the users comfort constraints as described in Section 3.4 . For instance, the scenario 1.1 shown in Fig. 7 , refers to the Aware macroscenario where only the winter set point was modified with respect to the reference scenario. Finally, all variables were changed at the same time in order to simulate the scenario described in Table 1 . In this way, it was possible to identify the most impactful parameters on energy consumption and on users comfort. Fig. 7 a shows the energy consumption prediction for each scenario. On the right side (Fig. 7 b), the monthly energy consumption for the three simulated scenarios and for the real case are plotted as a function of time. In particular, the gray line represents the reference scenario 0, the red one shows the unaware scenario 2, the green one refers to the aware user scenario 1 and the blue one the real energy consumption. On the left side (Fig. 7), instead, the annual energy consumption for each subscenario is plotted.

Table 1
Constraints for the three simulated scenarios.

	Set-point (heating period) ($^\circ C$)	Set-point (cooling period) ($^\circ C$)	Relative Humidity (%)	Brightness level (lux)	CO_2 concentration (ppm)
Reference Scenario					
Scenario 0	$21^\circ C$	$25^\circ C$	40-70%	500-700lux	700-1000ppm
Aware User Scenario					
Scenario 1	$19^\circ C$	$27^\circ C$	50-80%	500-550lux	800-1300ppm
Unaware User Scenario					
Scenario 2	$23^\circ C$	$24^\circ C$	40-50%	300-1000lux	500-700ppm



(a) Annual primary energy consumption for the various simulated scenarios.

(b) Primary energy consumption per month.

Fig. 7. Energy consumption for the Campus Luigi Einaudi derived from the dynamic energy simulation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.5. Results and considerations on comfort & energy

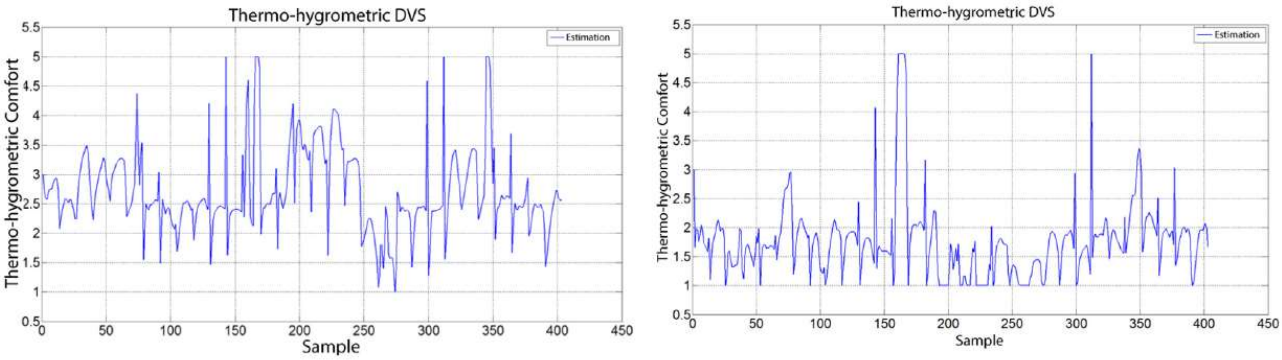
As a last step, we tested the set point limits for the three main scenarios, obtained from the energy and comfort simulations, with the developed thermo-hygrometric DVS trained with the users' feedback for a typical summer period. Thus, for the three scenarios with different temperature setpoints i.e. scenario 0 ($T = 25^\circ$), scenario 1 ($T = 27^\circ$), scenario 2 ($T = 24^\circ$) we respectively obtained an average thermo-hygrometric comfort of 2.3, 2.7 and 1.7. The comparison between the aware scenario and the unaware scenario is shown in Fig. 8 a and b. Notice that user comfort significantly increases in the aware scenario (2.7) with respect to the unaware scenario (1.7), moving from a generally discomfort situation (1 = very cold; 2 = cold) to a more comfortable configuration (3 = ok). By comparing these results on user comfort together with the energy simulation, described in Section 4.4 , it is possible to reduce energy consumption, from ∼410 kWh/m^2 (Scenario 2, Fig. 7) to ∼225 kWh/m^2 (Scenario 1, Fig. 7) and, meanwhile, to improve user comfort, from 1.7 to 2.7 (Fig. 8).

4.6. Considerations on living lab process

Overall, the large majority of the students involved during the codesign phase kept on participating during the following phase, when they were asked to provide comfort feedback during their university daily routine. In addition, more than 600 students, who did not take part in our laboratory, decided to join the experimentation. Users decided freely to join to the experimentation and sent feedback through the Mobile App. An ad hoc communication campaign was organized for each pilot building by sending an information email through the Departments' newsletters, by presenting the project and the Mobile App during the lectures or by organizing temporary stand in crowded places (e.g. bar, hall,). Thus, the engaged students were chosen randomly based on their needs to communicate their feelings (comfort/discomfort) or simply based on their interest in joining the experimentation. Generally, each student was free to send feedback at any time related to any classroom or laboratory within the pilot buildings, simply depending on his/her need to communicate his/her feeling. The communication initiatives were planned to avoid any possible bias on users, such as forcing reactions/feedback with incentives/penalties or other type of similar actions. In terms of the user engagement process, we noticed a lack of positive response to our communication input which was composed by a mixed approach of formal and informal channels, such as social media and official advertisements inside the buildings. Students did not react as expected to our proposal: it is necessary to take into account this not optimal response in order to avoid these mistakes in future research projects. Our suggestion to those who want to approach a crowdsensing research project is to put a great deal of effort in communication and engagement, in order to involve users in every stage of the experimentation. This is important because such innovative processes should not look like a top-down approach. Moreover, it is important to check in advance the compatibility between the technological level of the innovative proposal and the devices available on market and owned by involved users. In conclusion, it is recommended to plan a communication strategy involving the whole institution from the beginning. For instance, in a similar project any member of the university (e.g. students, researchers, academic and administrative staff) community should be aware that a project is taking place.

4.7. Considerations on users' engagement

We planned to further explore various aspects of the interaction between the occupants and the energy management of public buildings. The goal is to reach the decoupling of the energy consumption from indoor comfort, namely to reduce the energy consumption and related expenditure, while keeping comfort standards. In particular, we recognize the importance of developing strategies toward energy saving together with the energy management of the buildings involved, taking into account the features of the existing Building Energy Management Systems (BEMSs). Users' engagement remains a fundamental part of the project during all phases, from the design phase up to the adoption of new solutions. Beside the technical output, the living lab and the whole experimentation aims to improve the users' awareness about the energy issues related to socio-technical systems. If possible, occupants should also acquire new skills in their interaction with the building, like the use of thermoregulation devices, and become able to communicate with the energy management. Consequently, the improvement of users' awareness should lead to a general behavioural change [64] concerning energy and thermal practices. Pursuing this aim, it is important to take into account that users do not necessarily react to innovation in a positive way. In such research projects, researchers should avoid the so-called ABC models (Attitude Behaviour Choice [65]) where the social actors are thought to be able to improve their consumption practices toward a more sustainable behaviour just putting into actions useful tips provided by the researchers. On the contrary, it is necessary to reframe their consumption practices into a wider context where many social and technical variables can affect the performance. For instance, a good starting point is to consider the users as bounded into a socio-technical system [66] composed by both social and technical elements. In our case studies, buildings must be considered as socio-technical systems in which users are constrained, in everyday practices, by the limits given by the structure [67] .



(a) Aware scenario

(b) Unaware scenario

Fig. 8. Predicted results on thermo-hygrometric comfort obtained thanks to the Direct Virtual Sensor algorithm based on set point limits according to (a) aware and (b) unaware scenarios.

5. Conclusions

In this paper we have presented the results of a nine-month research project, Comfortsense, which took place at the University of Turin in 2015. The results presented here include the whole process, from the design of innovative technologies for the comfort and HVAC management and the development of an IT infrastructure, to the quantitative results on user comfort and energy consumption of HVAC systems. Thanks to comfort prediction we demonstrated that comfort and energy consumption can be partially decoupled adopting an adaptive indoor comfort management: a consistent reduction in energy consumption can be achieved taking into account real time, or predicted, feedback from users on Global, Thermal and Air Quality Comfort. In particular, by correlating the prediction on user comfort, i.e. the output of the Direct Virtual Sensor algorithm, with the output of the dynamic energy simulation, we proofed that modifying the HVAC and the energy management from the described “unaware”scenario to the “aware”scenario, the total annual energy consumption decreases from $\sim$410 kWh / m 2 to $\sim$225 kWh / m 2 and the indoor thermo-hygrometric comfort increase from 1.7 to 2.7 on a 1–5 scale, where 1 means too cold, 3 represents a good comfort and 5 is too hot. As far as an adaptive indoor comfort management is able to partially decouple indoor comfort from energy consumption in buildings with HVAC systems, further improvements on users’ engagement and the Living Lab process are needed. Better results in terms of users’ engagement, behavioural change and users-environment-management interactions could be obtained, adopting innovative solutions based on natural interactions [68] , point and click-interaction in smart environments [69] as well as designing and implementing gamification and rewards processes [70] . Finally, useful and necessary future works may be conducted to “close”the loop with a real-time automated process in order to improve our near real-time experimental case study.

Acknowledgement

The ComfortSense project was funded by the Piedmont Region thanks to the *“Bando regionale a sostegno di progetti di ricerca industriale e/o sviluppo sperimentale di applicazioni integrate e innovative in ambito Internet of Data IoD POR-FESR 2007–2013.”*

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi: 10.1016/j.enbuild.2019.01.007 .

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