An Intelligent System To Improve T-H-C Parameters At The Workplace

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UbiComp '16, September 12– 16, 2016, Heidelberg, Germany.

DOI string from ACM form confirmation

Abstract

Poor air quality and thermal comfort at the workplace affect the productivity, satisfaction and even health of employees, often without them being aware of the reason. This is a particularly problem in buildings without automated environmental controls, which are nowadays still in the majority. In this paper we present a system that uses an affordable and easy to install consumer weather station to monitor the temperature (T), humidity (H) and CO_2 concentration (C). Based on these, it estimates the number of occupants in a room and whether the windows are opened or closed. It uses this information together with knowledge stored in an ontology to recommend actions that improve the environment quality. Experimental evaluation showed that the system objectively significantly improves the T-H-C parameters, and that the occupants consider its recommendations subjectively appropriate.

Author Keywords

Smart office; Air quality; Monitoring; Ontology; Recommendation

ACM Classification Keywords

H.2.8 [Database Management]: Database Applications

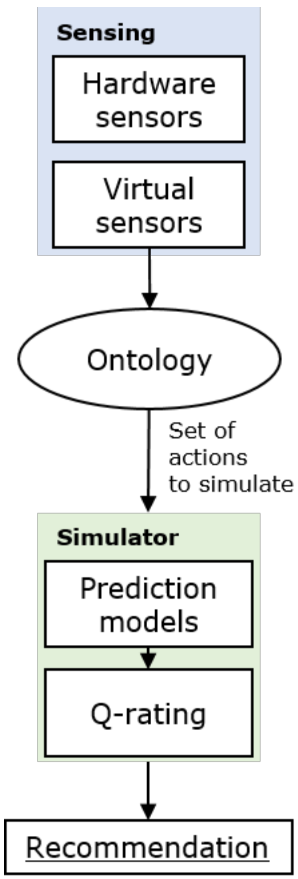

Figure 1: System architecture

Introduction

In this paper we present an intelligent system that monitors indoor temperature (T), humidity (H) and CO_2 concentration (C), and provides recommendations on how to improve these parameters. The system is intended for workplaces, where poor air quality not only affects health and well-being, but also significantly impacts productivity. The potential for increased productivity through improved air quality was estimated to around 20 billion USD in the USA [1]. The biggest issue are air pollutants, since they are difficult to detect subjectively — they can decrease the productivity by 6–9 % [5]. The impact of inappropriate temperature can be even higher — up to and sometimes above 10 % [3] — although it is easier to detect and usually also correct. The impact of inappropriate humidity is up to 5 % [3], but it is again more difficult to detect and correct.

The system presented in this paper is intended for workplaces without automated environmental controls, which are nowadays still in the majority and are expected to remain so in near future due to high costs of the equipment and the need for partial or full renovation. It uses an affordable and very easy to install consumer weather station to monitor T-H-C parameters. Note that one could build their own arduino/raspberry-pi weather station and connect it to our system. System provides recommendations on opening windows, adjusting heating etc. to occupants via a mobile application.

System description

The intelligent system to improve T-H-C has three major components - a sensing component, an ontology and a simulator, as shown in Figure 1. The sensing component is composed of hardware sensors and virtual sensors. The hardware sensors measure and return raw parameter values, while the virtual sensors use machine learning on the raw parameter values to estimate parameter values or device states that cannot be sensed directly. We have implemented occupancy estimator which estimates number of persons in the room and the window sensor. The outputs of the sensing component are fed into the ontology. A reasoner infers from ontology which actions can improve the state, based on the current state of parameters and present devices. The list of actions is fed into the simulator. The simulator is composed of a prediction module, which predicts the future changes of the T-H-C parameters, and the Q-rating module, which evaluates the quality of the environment. The overall task of the simulator is to simulate the effect of all the actions suggested by the ontology on the T-H-C parameters, and to return the action that results in the highest Q-rating.

The actions retrieved from the ontology can influence one or multiple monitored parameters. For example, turning up the humidifier influences only the humidity, whereas opening a window influences all the monitored parameters. To predict the values of the monitored parameters for each suggested action, we developed four machine–learning models for each of the T–H–C parameters. Four models are needed to predict the values for 15, 20, 25 and 30 minutes in the future, so that the simulator can consider different durations of the recommended actions (e.g. open the window for 15 or 20 minutes) producing total of 12 models. We define 1 time step to be equal to 5 minutes due to the hardware, which produces a new output every 5 minutes. The historic data of all the parameters from the previous 20 time steps along with the extracted features are fed into a regression algorithm, which outputs the predicted value. The used features are:

- Last measured values of indoor T–H–C

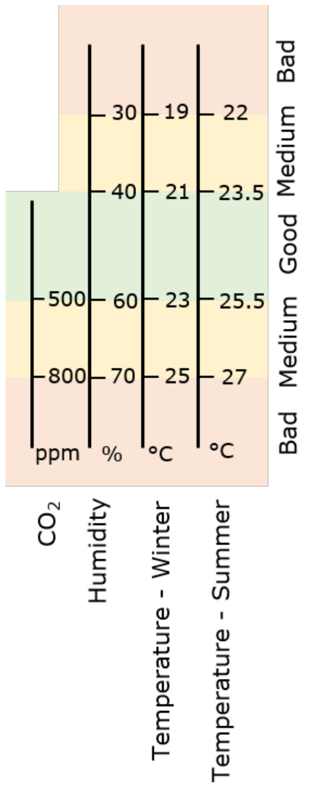

Figure 2: Comfort values. Good, medium and bad intervals are indicated in green, yellow and red, respectively.

- Last measured values of outdoor T–H
- Estimated number of occupants
- Estimated window state
- "First derivate" of each parameter, calculated over the last n time steps (n = 3, 5, 20) with the least square linear regression [2]
- "Second derivate" of each parameter, again calculated over the last n time steps (n = 3, 5, 20) with the least square linear regression [2], giving us the speed of the dynamics of the parameters
- The number of time steps since the last window action. This is important because parameter values change faster right after a window action was taken and then asymptotically approach a new equilibrium value.

We have evaluated multiple regression algorithms experimentally and selected the Support Vector Regression for all the prediction models. Each set of predicted parameter values for each suggested action in the next four time steps is fed into the Q-rating module for the evaluation of the environmental quality. The evaluation of the quality of the T-H-C parameters is based on the intervals defined by workplace regulations. They define the value intervals in which individual parameters are considered good, medium, or bad, as indicated in Figure 2.

The overall quality rating is composed of the ratings of the individual parameters as follows. The parameters which are good are assigned the value of 1. The parameters which are medium are assigned values between 0 and 1, and those which are bad values between 0 and -1, using linear scaling both in the medium and bad range (a cutoff value is assigned beyond which the rating is constantly -1). The overall quality is the average of all three parameter values and can range from -1 to 1.

Experimental evaluation

Dataset

Three offices, A (43 m^2), B (27 m^2), and C (20 m^2) were equipped for data collection and for the real-time validation of the recommendations. During the working hours (on work days between 9.00 and 17.00), the average number of occupants per office was: 2.6 ± 1.5 (max 9) in A, 2.0 $\pm$ 0.9 (max 7) in B and 1.6 ± 0.9 (max 7) in C. All offices were equipped with NetAtmo^{TM} indoor and outdoor modules [4], which measure several environmental parameters including T–H–C, a humidifier, window and door sensors that detected the window state as opened or closed, and with a smartphone application for self–reporting the occupancy, labeling the state of the devices (e.g., humidifier is on or off) and also for receiving recommendations about the best evaluated action from the system. The devices can be seen on Figure 3.

Since the measurements were obtained in winter time, air conditioning was never used. We started the collection of the data on 2016-01-16 and the collection is still in progress. We collected the data without any recommendations for the period from 2016-01-16 to 2016-02-26 (1st period), when the occupants were allowed to manipulate the room devices freely. For the period from 2016-02-26 to 2016-03-23 (2nd period) we installed the recommender system in office A, leaving the other offices without it. The occupants in office A followed the recommendations, while the occupants in the other offices continued using the devices freely. For the period from 2016-03-23 to 2016-03-30 (3rd period) offices A and B were equipped with the recommender system, leaving office C as a control office.

Figure 3: Devices used in the experiment. Indoor NetAtmo™ module (top left), humidifier (top right), window state sensor (bottom left), and application interface for self–reporting the occupancy, labeling the state of the used devices and receiving the recommendations (bottom right).

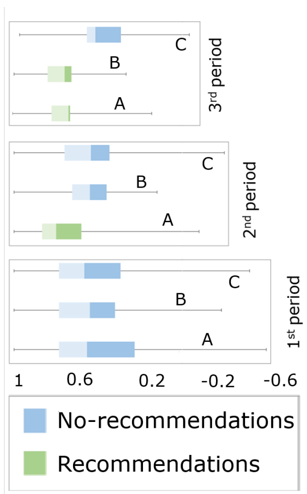

Figure 4: Overall Q–rating per office for all three periods. Blue boxes are offices without recommendations and green boxes are offices with recommendations.

	1st			2nd			3rd		
Office	A	B	C	A	B	C	A	B	C
Recomm.	✗	✗	✗	✓	✗	✗	✓	✓	✗
Temp.	.65	.59	.81	.76	.48	.73	.97	.95	.93
Hum.	.29	.35	.38	.50	.41	.29	.29	.35	.26
CO_2	.83	.94	.72	.93	.93	.78	.92	.91	.72
Overall	.59	.62	.64	.73	.61	.60	.73	.74	.64

Table 1: Q–rating of T–H–C parameters and the overall Q–rating during the three time periods for all the offices. The use of recommendations per office is marked for each time period.

Experiment and results

We first evaluated the objective performance of the recommendations by our system. At each time step, we calculated the comfort in terms of the Q–rating per parameter, and the overall Q–rating, both of which are presented in Table 1. Daily overall Q–ratings are presented in Figure 4 as a box chart. We evaluated the comfort over three time periods. We can observe that in first period all offices had comparable overall comfort and that office B was better at keeping the CO_2 at a good level due to frequently opening the windows, which resulted in poorer quality of the temperature. In Figure 4 we can see that the daily Q–ratings are on the same level for the first period. In the second period, the occupants of office A were using the recommendations and consequently the per–parameter quality and the overall comfort increased, while the comfort of offices B and C stayed similar to the first period. The daily Q–rating in office A also increased (Figure 4). In the third period, both offices A and B were using the recommendations and their comfort increased to a similar level, while the comfort in office C did not change significantly.

Conclusion

Results prove that using the system objectively improves the comfort. With the research we showed that we can obtain better environment quality without having expensive "smart–home" devices. It is hard by people alone to sense too low humidity or too high content of CO_2 if they are constantly in the same place for longer period. Users of experiment have subjectively approved system, they were satisfied with air quality in office during working hours and with price availability of the system.

Acknowledgments

The research was co-funded by the European AAL project Fit4work.

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