An Ontology-Based Thermal Comfort Management System In Smart Buildings

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ABSTRACT

Achieving thermal comfort for occupants in buildings has been the main focus of several studies in recent years. The challenging issue of the building envelope is to save energy and achieve a high comfortable environment simultaneously. To calculate the thermal comfort level in a living space, environmental factors such as indoor air temperature, mean radiant temperature, air velocity, and humidity are needed. The latter parameters are aggregated through the well known PMV index. In this paper, we introduce a wireless sensor network (WSN)-based comfort measurement approach, called OnCom, using a dedicated ontology and the emotional state analysis of the occupant to reach the "adequate" indoor thermal comfort. The main thrust of OnCom stands on the smooth connection of human emotions with the thermal sensations. Carried out experiments showed that emotions, unveiled from tweets, have been efficiently used to mitigate user thermal discomfort.

CCS CONCEPTS

• **Computing methodologies** → *Ontology engineering*.

KEYWORDS

Thermal Comfort; Wireless Sensor Networks (WSN); Smart Buildings; Ontology; Sentiment Analysis

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1 INTRODUCTION

Indoor comfort addresses a variety of issues, including thermal, visual and acoustic comfort as well as air quality. Comfort, by definition, is a state of mind, defined by the Cambridge Dictionary as "a pleasant feeling of being relaxed and free from pain". Indeed, comfort is the personal sensation of feeling comfortable. It is simply the absence of discomfort, which is certainly a feeling nice to have. Recently, we are witnessing an increasing demand by buildings occupants for the continuous monitoring of all indoor comfort related parameters. In this respect, the Internet of Things (IoT) is playing a major role by encompassing checking since the measure of connected devices and available information is always undergoing. Furthermore, thanks to these low-cost IoT based systems, we are able to monitor acoustic, olfactory, visual and thermal comfort levels. In the remainder, we put the focus on the thermal comfort, since it is an important indicator of overall building performance. Thermal comfort has become a hot topic issue in building performance assessment as well as energy efficiency. Three methods are mainly recognized for its assessment. Two of them, based on standardized methodologies, face the problem by considering the indoor environment in steady-state conditions (PMV and PPD) and users as active subjects whose thermal perception is influenced by outdoor climatic conditions (adaptive approach). The latter method is the starting point to investigate thermal comfort from an overall perspective by considering endogenous variables besides the traditional physical and environmental ones. Most of the surveyed approaches assess comfort condition by the use of the Predicted Mean Vote (PMV) [9].

In this paper, we introduce a new approach called OnCom, which is provided with different ambient sensors, computing, control and connectivity features. The main thrust of OnCom stands on the integration of the sentiment analysis to a smooth adjustment of the thermal comfort condition setting. Indeed, no one can deny that the worldwide diffusion of social media has profoundly changed the way users communicate and access information. Such a pervasive use of online social media provides a valuable knowledge that could not be neglected for the adjustment of the indoor thermal condition. The idea is to rely on the conjunctive research activities standing at the crossroads of microblogging, practitioners in natural language processing, machine learning and big data analysis to analyze opinions and unveil emotions conveyed by microposts [5]. The fine purpose of this analysis is to adapt the different SWRL rules used to adapt the indoor thermal condition.

The organization of the paper is as follows: Section 2 discusses the recent approaches that tackle the issue of monitoring thermal comfort in smart buildings. In section 3, we thoroughly describe the architecture of the proposed system. Section 4 describes the experimental study and the results we obtained. Section 5 concludes the paper and sketches avenues of future work.

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2 RELATED WORK

In the following, we provide a scrutiny of the pioneering works standing at the cross-roads of thermal comfort and sentiment analysis.

2.1 Thermal Comfort

Thermal comfort is defined as "*the state of mind which expresses satisfaction with the thermal environment*". It reflects the satisfaction of an occupant immersed in a thermal condition (ASHRAE 55 [1]). As mentioned by Fanger [11], the thermal comfort is influenced by six principal factors classified into objective and subjective variables. Air temperature, relative humidity, air velocity and radiant temperature are considered as objective. However, metabolic activity and clothing are examples of the subjective variables. In the sequel, the assessment of the thermal comfort is based on the most widely used index, which is Predictive Mean Vote (PMV) using the European Standard EN 15251 [9]. In the following, we sketch some of the recent approaches.

Torresani et al. [30] have developed a monitoring system, based on WSN, for the assessment of thermal comfort level of an indoor environment. In addition to basic sensors for air temperature and humidity measurements, the authors used in their studies, a set of transducers for better accuracy such as a radiant temperature sensor (for walls and floor temperature measurement) as well as a thermal mass flow sensor able to measure air velocity. In the same trend, Kumar and Hancke [20] have introduced a Smart Comfort Sensing System based on WSN according to international standards such as ASHRAE55-2013, ISO7730 and IEEE1451. The developed system measures temperature, humidity and CO2 in real-time to define the thermal and indoor air comforts. Later, Anand et al. [2] have proposed a system adjusting energy consumption and occupant's comfort (thermal comfort and air quality) in old buildings. To do so, the authors implemented a thermal comfort based algorithm for zonal damper control, an indoor air quality based window control and a light sensor based blinds control. The sensing and control action is based a WSN. Subsequently, Park and Rhee [24] have developed an IoT platform for smart buildings. Based on accumulated knowledge of the occupants, their individual health profiles are acquired by the system in order to provide them with better care services. The authors proposed a dynamic thermal model of occupants to reach the thermal comfort. The latter is based on the heat balance equation of human body and thermal characteristics of the occupants.

It's important to mention that, according to several studies, human working productivity [14, 15], occupant's moral [21] and potential health impairments [25] are in close connection with the thermal comfort. A lack of thermal comfort might cause stress among building occupants. Thus, the latter is considered as a critical parameter in building performance assessment. The scrutiny of the related work unveils the wealthy number of researches on this issue. Nevertheless, common weakness that can be addressed to the above mentioned works stands on the absence of the socio-psychological aspect of the occupant while achieving thermal comfort. Indeed, Yin et al. [33] highlighted that there is a close relationship between thermal comfort and meteorological environment, taking into consideration individual mood, gender, level of regular exercise, and previous environmental experiences.

2.2 Sentiment Analysis

Over the past decade, there has been an explosion of research works interested in sentiment analysis such as determining whether a sentence is objective or subjective; classifying a sentence as positive or negative; determining how strongly sentiments are expressed; detecting the emotion expressed in a sentence like happiness or disgust, applying sentiment analysis in healthcare, commerce, recommender systems, and other domains [6]. Surveys by [4, 19, 34] overview various sentiment analysis approaches from social networks and how it can be used to enhance information systems quality. We are interested in sentiment analysis state-of-the-art addressing two tasks: (*i*) detecting the polarity of online social texts; and (*ii*) determining the strength or the intensity of the expressed sentiment. Indeed, the most common sentiment analysis task is polarity detection. Lexical analysis technique was used in several former approaches and uses a dictionary containing pre-labelled lexicons like SentiWordNet [3], SenticNet [8], and so on. The input text is tokenized in tokens; that will be thereafter matched with the lexicon in the dictionary [5]. In the case of a positive match, the new score is added to the total score. Otherwise, this latter is decremented. Musto et al. have proposed in [22] a lexicon-based approach to identify the sentiment of Twitter messages. The proposed approach starts by splitting the target tweet into micro-phrases based on the splitting cues contained in the tweet like punctuation, adverbs and conjunctions. A prominent approach for sentiment analysis is based on the selection of a Machine Leaning algorithm and a feature extraction technique in order to train a classifier with a labelled corpus. This technique overcomes lexical techniques especially whenever the dictionary size grows exponentially. The authors in [13] have proposed a system of tweets classification based on three classifiers: the SVM, NB, and LR. The paper studied various combinations of features sets which can be used to represent tweets efficiently such as the information gain. Sentiment strength detection is less common and aims to predict the strength of positive or negative sentiment. Taboada et al. have developed a new calculator, called SO-CAL, which uses dictionaries, containing terms labeled with semantic orientation (polarity and strength), as well as valence shifters (negation, intensifiers, etc.) [28]. In [29], the authors estimate the emotional intensity based on a lexical algorithm. The proposed classifier SentiStrength2 uses both linguistic information and rules to detect sentiment strength from informal text. SentiStrength2 outputs two results: a score from 1 to 5 for positive sentiment strength and a score of -1 to -5 for negative sentiment strength.

2.3 Thermal Comfort and Emotional Experience

There is a natural connection between temperature and human emotional state [32]. For instance, studies in [16] proved that the manipulation of human's emotional state by the meaning of sad or happy events can affect thermal sensation. In the same context, the authors in [27] have presented a study which analyses the effect of personality traits (neuroticism, extraversion, and openness) on four human's behaviors, i.e., clothing adjustment, window opening, blind closing, and interactions with a ceiling fan and two thermal perception dimensions, i.e., sensation and preference. The findings prove that personality traits are significant to understand human's behavior. Indeed, thermal sensation was affected by the trait extraversion. However, thermal preference was affected by the trait neuroticism, openness and thermo-specific self-efficacy. Usually, emotional experience is classified through ratings associated to valence and arousal dimensions of Russell's circumplex model [26]. The authors in [32] have investigated emotions which could be transmitted by the thermal feedback. More specifically, they studied the mapping between ratings of thermal stimuli and the circumplex model. To do so, participants received several warming and cooling thermal stimuli to their hands and were invited to express their emotion and interpret it in terms of valence and arousal. In the following section, we introduce OnCom, which combines the use of an ontology and a sentiment analysis process to reach thermal comfort.

3 THE PROPOSED APPROACH

In the remainder, we introduce a wireless sensor network (WSN)-based comfort measurement approach, called OnCom, using the ontology and the emotional state of the occupant to reach the "adequate" indoor thermal comfort. The system has been designed as a three-layers platform to monitor and control the thermal comfort of an indoor environment. Based on several parameters such as humidity, temperature, air velocity, radiant temperature, luminosity as well as the emotional state, the system is able to automatically decide how to reach the thermal comfort level in real time. The design of proposed control system is depicted by Figure 3. The latter shows three layers: (*i*) the sensing layer; (*ii*) the semantic layer; and (*iii*) the controller layer. In the following, we thoroughly describe the above mentioned layers.

3.1 The sensing layer

In this layer, the system keeps track of the physical conditions of the environment through the wireless sensor network based on IoT technology. The most fundamental units of a WSN are sensor and actuator nodes. Both of them are coordinated and communicated by a virtual agent. The general architecture of a wireless sensor node is depicted by Figure 1. According to this figure, the node is composed by the following elements:

(1) **Sensors:** In OnCom, we use sensors for temperature, humidity, luminosity and wind speed. Every sensor has its characteristics. As we are dealing with more than one sensor in the nodes, we give more priority to the response time feature in the developed system. For instance the humidity sensor has a response time of 5 s, while the luminosity takes only 120 ms as a response time. In order to have correct results, the system takes into consideration these differences.
(2) **Actuators:** They are responsible for moving or controlling a mechanism. In our proposed system, we consider windows and blinds to be controlled by actuators. We use different types of actuators and they have to adapt with the controlled objects because have different shapes and different ways to close and open;
(3) **Node MCU:** It is considered as a communication modulus. It has the component ESP8266 which is a combination of a micro-controller and a microprocessor (central microcontroller unit) with a modulus WiFi (wireless communication). It allows the node to execute tasks including access to an Access Point(AP), access to the MQTT server, subscribe to the coordinator, take samples, calculate the mean, calculate the PMV index, calculate a maximum and minimum of comfort temperature and finally wait for the instruction to publish the collected data. The used protocol is a topic-based pub/sub protocol MQTT[1] ("Message Queuing Telemetry Transport");
(4) **Power Unit:** The consumption of energy of the battery is computed based on the characteristics of the sensor nodes. For instance, the node MCU has different modes (transmission, reception, deep sleep, active), the sensors have different power consumption and the actuators have batteries of continuous feeding;
(5) **Coordination Server:** The coordination between nodes allows a correct flow of data in the system. We use a Raspberry pi 3 as coordinator. The coordinator is responsible of communication between the nodes, giving instructions and storing data into a database.

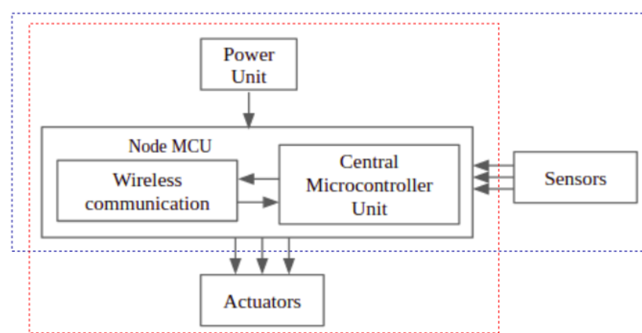

Figure 1: The general architecture of a Wireless Sensor Node: sensor node (blue), actuator node (red) (Source: an adapted figure from [7]).

3.2 The semantic layer

In order to semantically describe sensor data from the sensors network, we design a specific ontology for our system[2]. Based on Noy and McGuinness's methodology [10], the principle behind its design is to reuse and extend existing ontologies. Indeed, reusing external ontologies yields the advantage of using mature and proved ontological resources that have been validated through their applications by the W3C[3]. In the proposed system, we rely on the

[1] http://mqtt.org/
[2] http://ontology.oncom.checksem.fr/
[3] https://www.w3.org/

ssn/sosa[4], *event*[5], *geo*[6] and *qudt*[7] ontologies to describe the observation (collection of data) and actuation in a space of interest. The ultimate goal of these ontologies is to perform an actuation based on parameters such as temperature, radiant temperature, humidity, luminosity and air velocity in order to guarantee thermal comfort in a specific place. Temperature, humidity, radiant temperature, luminosity and air velocity are the observed parameters during the carried experiments. In this respect, according to them the ontology will act to guarantee comfort in the environments of interest. For example, if we consider to refresh the building, it is a common sense thought to open a window. Nevertheless, the parameters outside may sometimes limit these actions. It is worth mentioning that considering all possibilities of the parameters would take the ontology to establish many rules and act inefficiently. However, if we consider the rules of an action instead of rules for parameters, the task of action would be simplified. The full list of the SWRL rules of use during the reasoning phase is given in the appendix.

Example 1. *Let us consider the SWRL rule given by Figure 2. The latter highlights the relationship between an observation, an environment with an increase of temperature, the taken action resulting from this change as well as its limitations. The given rule explains that for each observation having an environment as a feature of interest, with a temperature greater than the maximum of the "temperature of comfort", implies opening the window located at the same place of the observation. However, the action is considered only if humidity and wind speed conditions (no rain and affordable wind speed) are appropriate. In the given case, the window is opened.*

```
sosa:Observation(?x) ∧ sosa:EnvironmentsSpace(?en) ∧
sosa:hasFeatureOfInterest(?x, ?en)∧oncom:TMIN(?en,
?tmin) ∧ oncom:TMAX(?en, ?tmax)∧
qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r)
∧ oncom:TEMP(?r, ?c) ∧ swrlb:greaterThan(?c, ?tmax)
∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en)∧
oncom:Windows(?win) ∧ sosa:hasFeatureOfInterest(?a,
?win) ∧sosa:ObservableProperty (?obsp) ∧
oncom:HMAX(?obsp, ?hmax) ∧ oncom:WINDMAX(?obsp,
?wmax)∧oncom:ParametersOutside(?po)∧oncom:HUM(?po,
?ho) ∧ swrlb:lessThan(?ho, ?hmax) ∧oncom:WIND(?po, ?ws)
∧ swrlb:lessThan(?ws, ?wmax) → oncom:OpenWindow(?a,
true) ∧oncom:ACTIVATE(?win, true)
```

Figure 2: One of the SWRL rule for thermal comfort.

3.3 The validation layer

There are innate links between human emotions and thermal sensation [32]. In other words, thermal sensation is a principal parameter in the modelling and experience of emotion. Indeed, physical warmth increases social and interpersonal warmth [17, 31] and the experience of physical temperatures helps to ground and process emotional experience [18]. In this layer, we use user's sentiment polarity and strength to measure his/her degree of satisfaction towards the action taken by the system, e.g., close window, open windows, etc. We instantly analyse the user's online message extracted from Twitter to determine whether (s)he is satisfied or not.

The different steps of our validation layer, are described below:

(1) **Tweet extraction:** Tweets are collected using the Twitter4j[8] API. The user ID or the screen name of a given user are provided to the get_favorites() function of the rtweet package in order to extract his/her last status;
(2) **Tweet cleaning:** Unlike to emotional texts in classical online sources like emails, web reviews, blogs, etc., micro-blogs have some particularities that should be understood before the use of their information. First, micro-blogs are usually consulted from mobile devices having a limited display zone that defines a limited strength. So, users face input difficulties. In addition, some micro-blogs define a limited statuses length, e.g., tweets are restricted to 280 characters. Thus, user publications are more likely to contain misspellings, informal words, short form texts and interjections. As a result, micro-blogs text mining systems need to pass through a pre-treatment step to make status texts able to be processed by natural language processing systems. In our validation layer, tweets are first tokenized in order to extract words (terms, usernames, numbers, URLs, hashtags, etc.) based on spaces and punctuation marks. Next, tweets are filtered by removing usernames, stop-words, retweet signs, numbers, special characters, and URLs from the constructed bag of words. Next, the concatenated words of hashtags are separated based on the fact that hashtag words begin with an uppercase letter, e.g., #IFeelSoHot. Finally, words spelling is checked using a dictionary;
(3) **Tweet classification:** The objective of tweet classification is to determine the polarity (positive, negative or neutral) and the intensity (the sentiment score) of a particular tweet. We use SentimentAnalysis[9] R package for the classification task. This package utilizes several dictionaries, like QDAP, Harvard IV and Loughran-McDonald.

4 EXPERIMENTS AND RESULTS

Nielsen and Landauer have showed that 5 users are sufficient to get the best results in finding the majority (about 80%) of usability problems of a system [23]. However, in [12], Faulkner has demonstrated the risk of the restriction to a set of randomly selected 5 users, i.e., sometimes 5 participants only found 55% of the problems. According to him, the lowest percentage of problems revealed with 10 users is always better than 80%.

In this paper, we run our tests with 11 participants heterogeneously distributed by age, gender and educational background. Table 1 (left) shows some statistics about participants including the participant ID, his/her age, his/her gender and the number of his/her tweets. Each participant is invited to express his/her opinion, in each of the 14 situations described in Table 3, towards the

[4]https://www.w3.org/TR/vocab-ssn/
[5]http://purl.org/NET/c4dm/event.owl#
[6]http://www.w3.org/2003/01/geo/
[7]https://qudt.org/
[8] http://twitter4j.org
[9]https://cran.r-project.org/web/packages/SentimentAnalysis/vignettes/SentimentAnalysis.html

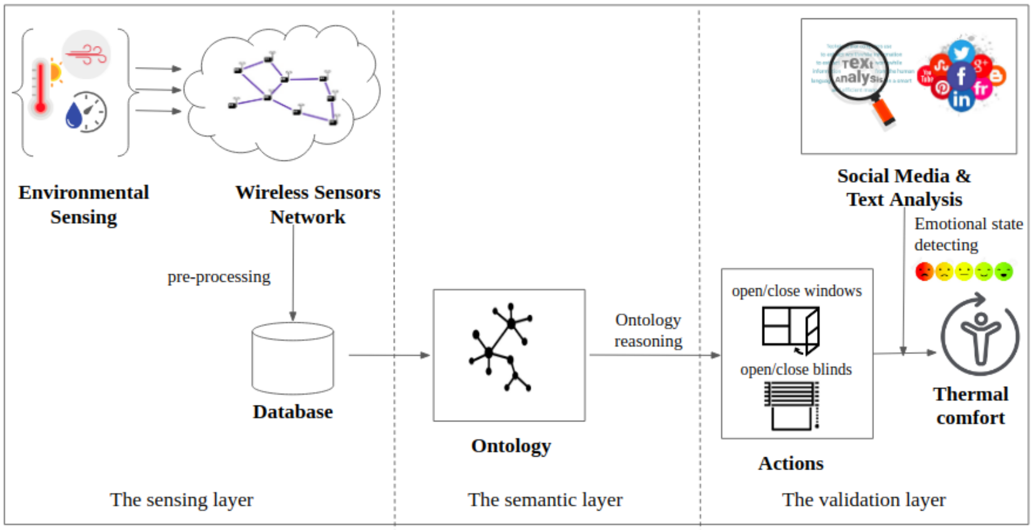

Figure 3: Overall OnCom architecture at a glance.

action taken by the system. We have collected a total of 154 tweets, i.e., 14 tweets by participant. A sample of the tweets expressed by participants, in situation S1, is depicted by Table 1 (right).

As shown, in Table 3, we have selected, on the 18^{th} of July, different situations characterized with various values of Temperature, Humidity, Radiant temperature, Wind speed, Luminosity and PMV. For each situation, we have applied our wireless sensor network (WSN)-based comfort measurement approach OnCom to select the appropriate action which can enhance the user's level of thermal comfort. The action can change the state (open or close) of the window, blinds (e.g., $S1$, $S6$, $S13$ and 14) or keep the same state (e.g., $S2$, $S3$, etc.). Next, we have applied our sentiment analysis approach to get the polarity and the intensity of the sentiment expressed in the user's tweet. The classification results are interpreted to measure participants' satisfaction. The results of our sentiment classification are shown in Table 2. The latter shows that the mean of users' judgments about the actions taken by the system are almost positive. Indeed, only in situations $S11$, $S13$ and $S14$ opinion means were negative. However, in the 11 other situations, means of participants judgments are positive. So, we can notice that, in most cases, the actions taken by the system were judged as correct by particiants. For example, in the first situation $S1$, only the tweet of the user $U8$, saying "I may need another iced coffee lol fuck. #coffeeaddict #hotday" towards the action "OpenBlinds" is classified as negative with an intensity of -0.111 and the mean of all participants judgments is about 0.171. In some cases, tweets was classified as neutral. For example, in $S14$, the participant $U11$ have expressed his need for food by the tweet "Hungry AF". In this case, the tweet has no relation with the thermal comfort of the user. So, it can not be classified as positive or negative. In many other situations, such as $S3$, $S5$ and $S6$, all the participants were satisfied by the actions "KeepState" and "CloseBlinds".

5 CONCLUSION

In this paper, we proposed an efficient system for optimizing the occupant's thermal comfort in smart buildings. For this purpose, we combined the use of the ontology and the emotional state. In the developed system, inference rules provide intelligent assistance to decide about the appropriate action for maintaining the indoor thermal comfort. Then, a sentiment analysis process is enabled in order to validate the taken action. In the near future, we plan to scale up our validation layer by using a larger dataset. Indeed, we have used in our experiments a population of 11 participants. It will be interesting to collect extra tweets to check the effectiveness of the proposed system. We also plan to use participants' opinions as feedbacks to improve in real time the action selected by our approach OnCom.

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[10]http://www.wittym.com/

Table 1: (Left) Participants statistics; (Right) A sample of the tweets written by User 1 to express his opinion towards the actions taken in the 14 situations.

User	Gender	Age	Position	Educational background	# Tweets
User 1	Male	28	Data Scientist	PhD degree	14
User 2	Female	27	PhD student	Engineer's diploma	14
User 3	Male	25	PhD student	Engineer's diploma	14
User 4	Female	28	PhD student	Master's degree	14
User 5	Male	26	Engineer	Engineer's diploma	14
User 6	Male	31	Project Manager	Master's degree	14
User 7	Male	28	PhD student	Master's degree	14
User 8	Male	26	Engineer	Engineer's diploma	14
User 9	Female	25	Engineer	Engineer's diploma	14
User 10	Male	23	Technician	Technician's diploma	14
User 11	Male	23	Technician	Technician's diploma	14

Situation	Tweet
S1	#work#work#work#tired :(
S2	#workhard#be proud :)
S3	no need to cry#wonderful life
S4	keep calm#work hard#motivation
S5	I need a coffee pleeaaaaaase
S6	I want some breakfast
S7	huuuuungryyyyy
S8	Feeling in a #happymood #happy
S9	#happymood #goodvibe
S10	Everything is purple
S11	Oh yeah
S12	FINALLY
S13	I want some ice cream
S14	I Feel Like Dancing# PartyMood

Table 2: Sentiment analysis results in terms of polarity and intensity.

User	Situation													
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**S11**	**S12**	**S13**	**S14**
U1	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.333	0.000	0.000	0.000	0.000	0.000	0.250
U2	0.666	0.666	0.222	0.000	1.000	0.000	0.333	0.000	0.666	0.000	0.000	1.000	-0.500	0.000
U3	0.500	0.000	0.000	0.666	1.000	0.500	0.250	0.666	0.000	0.857	0.000	0.333	0.000	0.000
U4	0.000	-0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.500	0.000	-1.000	0.333
U5	0.333	0.000	0.500	-0.500	0.333	0.000	0.000	0.333	0.000	0.500	0.000	-0.143	0.000	0.285
U6	0.000	0.333	0.333	0.666	0.333	0.333	0.000	0.000	-0.666	0.000	-1.000	0.000	-1.000	-1.000
U7	0.000	0.000	0.166	0.500	1.000	1.000	1.000	0.000	0.000	-1.000	0.000	0.000	-0.600	0.000
U8	-0.111	0.333	0.166	-0.500	1.000	0.500	0.500	-0.333	0.000	0.500	0.000	0.000	0.000	0.000
U9	0.000	0.250	0.000	0.000	0.000	1.000	1.000	0.000	0.500	0.500	0.333	0.333	0.000	-1.000
U10	0.500	0.500	0.000	0.000	0.000	0.000	0.333	0.000	0.500	0.750	-0.333	0.000	0.000	-0.500
U11	0.000	0.000	0.000	-0.500	0.000	0.500	0.333	0.000	-0.500	0.000	0.000	0.000	0.333	0.000
Mean	0.171	0.189	0.164	0.030	0.424	0.348	0.341	0.091	0.045	0.237	-0.045	0.138	-0.251	-0.208

Table 3: Experimental results (18-07-2019).

Situation	Time stamp (hh:mm:ss)	Temperature (C°)	Humidity (%)	Radiant temperature (C)	Wind speed (m/s)	Luminosity	PMV	Action
S1	08:06:19	27.87	29.52	28.00	0.1	2315.00	0.73	OpenBlinds
S2	08:16:01	24.29	37.67	24.40	0.1	3977.50	-0.67	KeepState
S3	08:25:45	23.36	38.89	23.30	0.1	4337.42	-0.56	KeepState
S4	08:35:31	23.22	38.54	23.00	0.1	4790.08	-0.63	KeepState
S5	08:45:20	25.37	34.21	25.20	0.1	4890.42	-0.01	KeepState
S6	08:55:06	25.07	33.45	24.92	0.1	3889.58	-0.08	CloseBlinds
S7	09:04:50	23.61	36.41	23.24	0.1	3549.00	-0.54	KeepState
S8	09:14:36	23.95	37.54	23.50	0.1	4150.75	-0.44	KeepState
S9	09:24:21	23.91	38.04	23.60	0.1	4569.92	-0.44	KeepState
S10	09:34:10	24.17	37.68	24.20	0.1	5149.33	-0.32	KeepState
S11	09:43:56	24.71	36.48	24.20	0.1	5754.08	-0.23	KeepState
S12	09:53:41	25.25	35.39	25.10	0.1	5754.58	-0.03	KeepState
S13	10:03:32	25.91	34.19	25.50	0.1	5615.83	0.12	OpenBlinds
S14	10:13:21	26.26	33.30	26.00	0.1	2594.00	0.24	OpenWindow

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High Temperature:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en)∧ oncom:TMIN(?en, ?tmin) ∧ oncom:TMAX(?en, ?tmax) ∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ TEMP(?r,?c) ∧ swrlb:greaterThan(?c, ?tmax) → oncom:UncomfortablePlaces(?en)

High Humidity:
− sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ oncom:HUM (?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:HIMAX(?obp,?himax) ∧ swrlb:greaterThan(?c, ?himax) → oncom:UncomfortablePlaces(?en)

High Luminosity:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en)∧ qudt-1-1:QuantityValue(?r)∧sosa:hasResult(?x, ?r) ∧ oncom:LUM(?r, ?c) ∧oncom:ObservableProperty(?obp) ∧ oncom:LMAX(?obp, ?lmax) ∧ swrlb:greaterThan(?c, ?lmax) → oncom:UncomfortablePlaces(?en)

Low Luminosity:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ oncom:LUM(?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:LMIN(?obp, ?lmin)∧ swrlb:lessThan(?c, ?lmin) → oncom:UncomfortablePlaces(?en)

Low Humidity:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en)∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧sosa:hasResult(?x, ?r) ∧ oncom:HUM(?r, ?c) ∧ sosa:ObservableProperty(?obsp) ∧ oncom:HIMIN(?obsp,?himin) ∧ swrlb:lessThan(?c, ?himin) → oncom:UncomfortablePlaces(?en)

Low Temperarture:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ sosa:TMIN(?en, ?tmin)∧ sosa:TMAX(?en?tmax)∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ TEMP(?r,?c) ∧ swrlb:lessThan(?c,?tmin)→ oncom:UncomfortablePlaces(?en)

Close Windows:
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ sosa:TMIN(?en, ?tmin) ∧ sosa:TMAX(?en,?tmax)∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ sosa:TEMP(?r,?c) ∧ swrlb:lessThan(?c, ?tmin) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧ oncom:Windows(?win) ∧ sosa:hasFeatureOfInterest(?a,?win) →oncom:CloseWindow(?a, true) ∧ oncom:ACTIVATE(?win, true)
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧sosa:hasResult(?x, ?r) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧oncom:Windows(?win) ∧ sosa:hasFeatureOfInterest(?a, ?win) ∧oncom:ParametersOutside(?po) ∧ oncom:HUM(?po,?ho)∧ oncom:ObservableProperty(?obp) ∧oncom:HMAX(?obp, ?hmax) ∧ swrlb:lessThan(?ho,?hmax)→ oncom:CloseWindow(?a, true) ∧ oncom:ACTIVATE(?win,true)
−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧sosa:hasResult(?x, ?r) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧oncom:Windows(?win) ∧ sosa:hasFeatureOfInterest(?a, ?win)∧ oncom:ParametersOutside(?po) ∧ oncom:WIND(?po, ?wo) ∧ oncom:ObservableProperty(?obp) ∧oncom:WMAX(?obp, ?wmax) ∧ swrlb:lessThan(?wo,?wmax)→ oncom:CloseWindow(?a, true) ∧ oncom:ACTIVATE(?win,true)

Open window:
−sosa:Observation(?x) ∧ sosa:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ oncom:TMIN(?en, ?tmin) ∧ oncom:TMAX(?en, ?tmax)∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ oncom:TEMP(?r, ?c) ∧ swrlb:greaterThan(?c,

?tmax) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧ oncom:Windows(?win) ∧ sosa:hasFeatureOfInterest(?a, ?win) ∧ sosa:ObservableProperty (?obsp) ∧ oncom:HMAX(?obsp, ?hmax) ∧ oncom:WMAX(?obsp, ?wmax)∧ oncom:ParametersOutside(?po) ∧ oncom:HUM(?po, ?ho) ∧ swrlb:lessThan(?ho, ?hmax) ∧ oncom:WIND(?po, ?ws) ∧ swrlb:lessThan(?ws, ?wmax)→ oncom:OpenWindow(?a, true) ∧oncom:ACTIVATE(?win, true)

Open Blinds:

−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧oncom:TMIN(?en, ?tmin) ∧ oncom:TMAX(?en, ?tmax)∧qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧oncom:TEMP(?r,?c) ∧ swrlb:lessThan(?c, ?tmin) ∧ sosa:Actuation(?a) ∧hasLocation(?a, ?en) ∧ oncom:Blinds(?bli) ∧ sosa:hasFeatureOfInterest(?a, ?bli) ∧ oncom:ObservableProperty (?obp) ∧ oncom:LMAX(?obp, ?lmax) ∧ oncom:ParametersOutside(?po) ∧ oncom:LUM(?po, ?lo) ∧ swrlb:lessThan(?lo, ?lmax) → oncom:OpenBlinds(?a, true) ∧oncom:ACTIVATE(?bli, true)

−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧sosa:hasResult(?x, ?r) ∧ oncom:LUM(?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:LMIN(?obp, ?lmin) ∧ swrlb:lessThan(?c, ?lmin) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧oncom:Blinds(?bli) ∧ sosa:hasFeatureOfInterest(?a, ?bli) → oncom:OpenBlinds(?a, true) ∧ oncom:ACTIVATE(?bli, true)

CloseBlinds:

−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧sosa:hasResult(?x, ?r) ∧ oncom:LUM(?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:LMAX(?obp, ?lmax) ∧ swrlb:greaterThan(?c, ?lmax) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a,?en) ∧ oncom:Blinds(?bli) ∧ sosa:hasFeatureOfInterest(?a, ?bli)→ oncom:CloseBlinds(?a, true)∧ ACTIVATE(?bli, true)

Lights ON:

−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧ oncom:LUM(?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:LMIN(?obp, ?lmin) ∧ swrlb:lessThan(?c, ?lmin) ∧ sosa:Actuation(?a) ∧ sosa:hasLocation(?a, ?en) ∧oncom:Lights(?lig) ∧ sosa:hasFeatureOfInterest(?a, ?lig) ∧ oncom:ParametersOutside(?po) ∧ oncom:LUM(?po, ?lo) ∧ swrlb:lessThan(?lo,?lmin) → oncom:TurnON(?a, true) ∧ oncom:ACTIVATE(?lig, true)

Lights OFF:

−sosa:Observation(?x) ∧ oncom:EnviromentsSpace(?en) ∧ sosa:hasFeatureOfInterest(?x, ?en) ∧ qudt-1-1:QuantityValue(?r) ∧ sosa:hasResult(?x, ?r) ∧oncom:LUM(?r, ?c) ∧ oncom:ObservableProperty(?obp) ∧ oncom:LMIN(?obp, ?lmin) ∧ swrlb:greaterThan(?c, ?lmin) ∧ sosa:Actuation(?a) ∧ oncom:hasLocation(?a, ?en) ∧ oncom:Lights(?lig) ∧ sosa:hasFeatureOfInterest(?a,?lig) ∧ oncom:ParametersOutside(?po)∧ oncom:LUM(?po, ?lo) ∧swrlb:greaterThan(?lo, ?lmin) → oncom:TurnOFF(?a, true)∧oncom:ACTIVATE(?lig, true)

StateObjects:

−oncom:Blinds(?bli) ∧ oncom:ACTIVATE(?bli, true)→ oncom:ChangeStateOfObjects(?bli)

−oncom:Lights(?li) ∧ oncom:ACTIVATE(?li, true)→ oncom:ChangeStateOfObjects(?li)

−oncom:Windows(?win) ∧ oncom:ACTIVATE(?win, true)→ oncom:ChangeStateOfObjects(?win)