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IOT ANALYSIS AND MANAGEMENT SYSTEM FOR IMPROVING WORK PERFORMANCE WITH AN IOT OPEN SOFTWARE IN SMART BUILDINGS

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Abstract

With the aim of investigating the effect of climate on the heating in buildings and human productivity, the data of thermal sensors distributed at rooms and buildings level were sent to an implemented analytic management system. This latter integrated an Internet of Things (IoT) open-source software. As part of the smart buildings project, the challenge here is to analyze the aggregated data. Therefore, statistical methods were applied to study the relationship between climate and environmental parameters of the HFT University buildings in the city Stuttgart (Germany) during 2016. Moreover, we studied the effect of indoor temperature on the thermal sensation at the same location. To optimize the result, this study was limited to workdays and cold seasons.

Keywords: *Internet of Things (IoT), buildings performance, workplace performance*

1. Introduction

Climate change is one of the major technological, economic, and environmental challenges for highly efficient buildings [6]. Nowadays, the thermal systems, in many commercial buildings, are not controlled well, due to many factors, for example, improper control system design or operation, heating, and cooling capacity, etc. Much evidence shows that the buildings services performances depend strongly on the indoor environmental conditions, which in turn strongly affect the health and productivity of workers [1], [2], [3], [4], [5], [11]. On a local scale, this can be improved using common building automation bus systems [12], [13], and technology.

In our research study, we aim to analyze the monitored environmental data in order to improve buildings' energy and occupant's efficiency in the workplace at the HFT Stuttgart University of Applied Sciences in Germany. Furthermore, we show the benefits to add conditions such as seasonal filtering and rooms' occupation for purposes of optimizing resource utilization. Therefore, the use of the Internet of Things (IoT) to the field is investigated.

In recent years, IoT technologies have become the base of most modern technological achievements, and one of the biggest sources of data. The IoT incorporates transparently, smoothly numerous, and heterogeneous end systems [17]. The huge number of data generated by the IoT telemetry sources are used for statistical analysis, prediction, or critical decision in various applications of different areas (health, energy, buildings, districts, etc.). Moreover, IoT back end systems present data on different widgets with easy access. Therefore, the data analysis and other IoT services can provide regional test samples related to the consumption, emissions, and usage state as well as the conditions of buildings' thermal isolation. In the long run, it is also expected to attain indications on the workplace's performance. However, the heterogeneity of devices, different thermal conditions, workers' productivity performance, and no actual existence of a general climate control system: all make a list of important topics to be handled as main challenges in this field.

The paper is organized as follows: In Section 2, we present, in-depth, a short comparative study to choose the more appropriate IoT tool. In Section 3, we introduce the designed IoT Tool. Taking into consideration environmental performance conditions, we present in Section 4 the environmental data and use cases evaluating proposed technology to perform occupant thermal sensation at workplaces. A summary concludes our findings (Section 5).

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2. State of the Art

Nowadays, the utilization of IoT solutions in different service domains such as monitoring and visualization is increasing. In [14], they have compared some best known IoT platforms that help to develop the IoT projects in a controlled way.

Table 1. Open source IoT platforms comparison.

IoT Software	Integration	Data Collection	Analyses	Visualization	Data Base
Thingsboard	REST APIs, MQTT APIs	HTTP, MQTT, OPC-UA,CoAP	Real time analytics (Apache Spark, kafka)	Yes	PostgreSQL, Cassandra, HSQLDB
Kaa	Portable SDK available to integrate any particular platform, REST API	MQTT, CoAP, XMPP, TCP, HTTP, WiFi, Ethernet, Zigbee	Real time	Yes (Doesn't have own dashboards) NoSQL	MongoDB, Cassandra, Hadoop, Oracle
WSo2	REST APIs	HTTP, WSO2 ESB, MQTT	Yes, WSO2 Data Analytics Server	Yes	Oracle, PostgreSQL, MySQL, or MS SQL
Site Where	REST API	MQTT, AMQP, Stomp, WebSockets, and direct socket connections	Real-time analytics (Apache Spark)	No	MongoDB, HBase, InfluxDB
Thing Speak	REST API, MQTT APIs	HTTP	MATLAB Analytics	No	MySQL
DeviceHive	REST API, MQTT APIs	REST API, WebSockets or MQTT	Real-time analytics (Apache Spark)	Yes (Doesn't have own dashboards)	PostgreSQL, SAP Hana DB
Zetta	REST APIs	HTTP	Using Splunk	No	Unknown
Distributed Services Architecture (DSA)	REST APIs	HTTP	No	No	ETSDB Embedded Time Series
Thinger.io	REST APIs	MQTT, CoAP and HTTP	Yes	No	MongoDB

They have defined main parameters that helped us to make an efficient research decision:

- The IoT must be an open-source;
- Able to install on cloud or own server;
- Support a variety of protocols;
- External integration;
- Analyzing and Visualization tools.

The initial results (see Table[1]) showed that, from the nine open-source IoT software illustrated above, there are only four platforms providing visualization support: ThingsBoard, Kaa IoT, WSo2, and DeviceHive. The visualization support is an important prerequisite, it offers the capacity to see and analyze data via dashboards. Thereafter, comparing the four aforementioned tools, we assume that only ThingsBoard and WSo2 have the ability to create and manage their own Dashboards, the other tools seem to need external tools to generate dashboards. Subsequently, comparing ThingsBoard and WSo2, we estimated that the first one, ThingsBoard, has better adaptability. It uses main protocols IoT, including OPC-UA. Here, we assumed that ThingsBoard offered better features to be selected. In the following, we started our study of the platform.

ThingsBoard [15] is an open-source IoT platform for data collection, processing, visualization, and device management. It is based on Java 8. It acts as an IoT gateway between registered devices communicating by the mean of protocols like HTTP, CoAP, and MQTT. It provides the administrator or tenant user with a rich web interface to define and manage devices. Each device is represented by a unique access token so it can be organized by its profile and ownership.

ThingsBoard allows defining rules, that can be applied to incoming messages and plugins. Typical operations that could be implemented by means of rules are comparisons between the received values and some static threshold (to check, for instance, if the temperature has exceeded a safety threshold).

ThingsBoard offers the ability to perform interoperability among heterogeneous containers, named assets, around us. We can also define alarms for assets and devices: they can be used to send notifications during the processing phase.

ThingsBoard gives also the possibility to use/create dashboards. those latter can be customized with more than 30 widgets. A typical dashboard can include, for instance, data like line chart to show time series data, map to locate a monitored place, or gauge bar to show single value.

3. System Setup

After comparing the IoT Platforms, choosing the best option, studying, and resuming different features, we made it possible to present ThingsBoard as a solution for our IoT environment. On the other hand, these do not support completely the potential goal and use case introduced in Section 1. Therefore, this work aimed to present the feasibility of developing a regional IoT tool of the networked building climate system and occupant's performance. For that reason, we integrated only ThingsBoard's functionalities in this tool.

Our designed system provided central monitoring and tracking temperature of rooms in several buildings at the HFT Stuttgart University. The IoT architecture described in this paper is based on the ThingsBoard IoT platform. The proposed IoT architecture is illustrated in Fig. 1. This architecture consists of three levels:

- level 1 is the data aggregation phase,
- level 2 is the data process and ThingsBoard integration phase,

- and level 3 represent the data visualization and analyzes phase.

We show also the benefits of integrating conditions context data such as season of the year or rooms' occupation for purposes of optimizing resource utilization.

To implement an IoT management system for building environmental data and workplace performance, sensors were used. The aggregated data sent to a central monitoring database at the HFT University of Stuttgart, with a one-hour delay between two values. The aggregated environmental data represented by the temperature measurements, like outdoor, indoor, and heating temperature. Outdoor temperature is the outside ambient air temperature, the indoor temperature is the room temperature, and the heating temperature is the temperature of the radiator.

We developed an interface connected to the database pool. It acts as a filter to export specific parts of our collected data. With this filter, we choose for example sensors types (like temperature, humidity, Co2, etc.), the resources descriptions (like indoor temperature, thermostat, etc.), location (room, building, etc.) and may also specify other factors. As a result, a list of identified resources and their values for the specified period, whether to export the output to an Excel spreadsheet.

In this research study, for instance, we analyzed the temperature of one room at the HFT University of Stuttgart during the cold season 2016, this room named 'Aula'. Therefore, we choose the data collected by the thermal sensors, in Aula, during 2016. Thereafter, to minimize the size of analyzed data and optimize our evaluation method, we choose the working days to be analyzed and partitioned the cold season in two parts: part 1 representing the period from January 2016 till March 2016, and part 2 from September 2016 till December 2016.

In this paper, a top-down model [16] is used. The top-down modeling approach, typically, work on historical time series to analyze the variation of aggregated data. This model has been adopted to correlate temperature parameters of buildings to weather variations. A Python script sent the exported data, via MQTT, to ThingsBoard in JSON strings, Where measured parameter values are represented by key-values-pairs. The JSON string of a typical client message could be:


```
{"Timestamp": 1451606400000.0,
 "values":{
            "Room" : "Aula",
            "Indoor-Temp": 20.568,
            "Heating-Temp": 36.378,
            "Outdoor-Temp": 4.913
     }
}
```


At ThingsBoard level, the data are visualized by the mean of the dashboard (Fig.2). We created dashboards using existing widgets and acting as administrator/customer interface to locate our assets on the map, visualize and manage the environmental data state at selected building/floor/room at the HFT University according to predefined constraints and thresholds. ThingsBoard illustrates the monitored data by the mean of dashboards. Dashboards were created by using the different existing widgets of ThingsBoard, these dashboards (Fig. 2), were used as user interfaces. In Thingsboard, before dashboards creation, we have to determine the different assets and devices. Here, the main asset is Stuttgart city of Germany, defined with type district, a ThingsBoard's widget map was used to locate the Stuttgart city. This asset contains other assets representing the different commercial/ public buildings. Here, there are the HFT University Buildings. Fig. 2 shows the corresponding dashboard, which contains a map widget to locate these Buildings. In Fig. 2, on the right side of the map's widget, the table illustrated the different buildings of the University (Building1, Buildings2, etc.). Surfing from table to table, we found Aula in the Building1 with other Floors and Rooms' description. By choosing Aula, a new dashboard is opened that contains the different widgets: chart widget, Alarm widget, thermostat Setpoint widget, together to visualize the ambient state of the selected room: Aula.

In the next section, we investigate the use case to evaluate the thermal sensation from the collected data at 'Aula'.

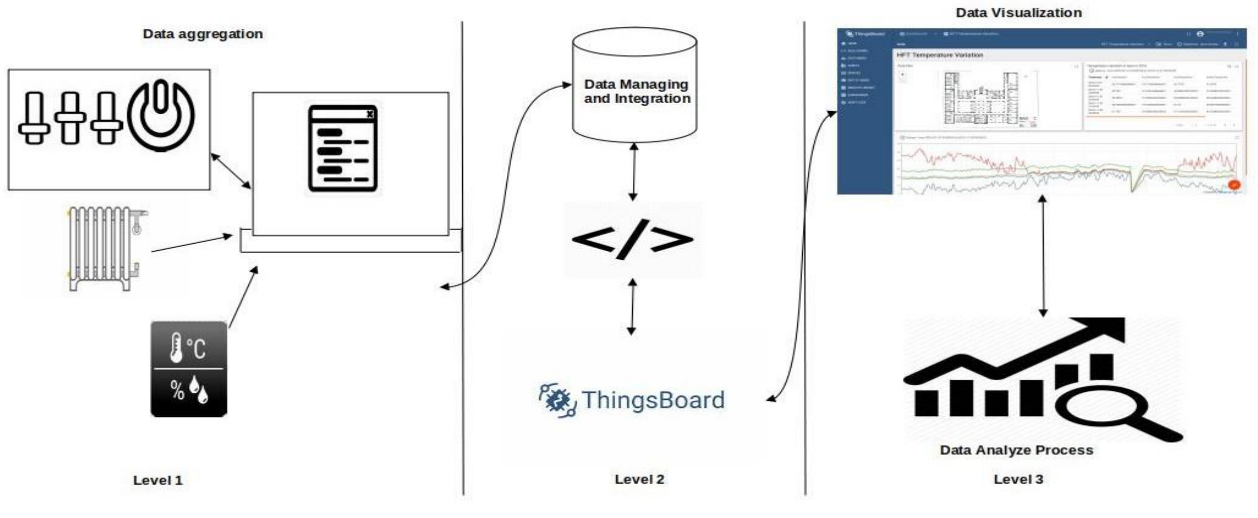

Fig. 1.System Architecture

Table 2. Physical measurements (min, max, mean) describing the environmental conditions under the two exposure seasonal

Conditions (Seasonal parts)	Outdoor Temperature(°C)			Indoor Temperature (°C)			Heating Temperature (°C)		
	Min	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*
Part 1	-3.103	14.679	6.460	18.26	25.58	20.32	27.61	54.44	44.32
Part 2	-2.581	18.398	8.865	18.23	25.32	21.10	23.85	54.69	38.30

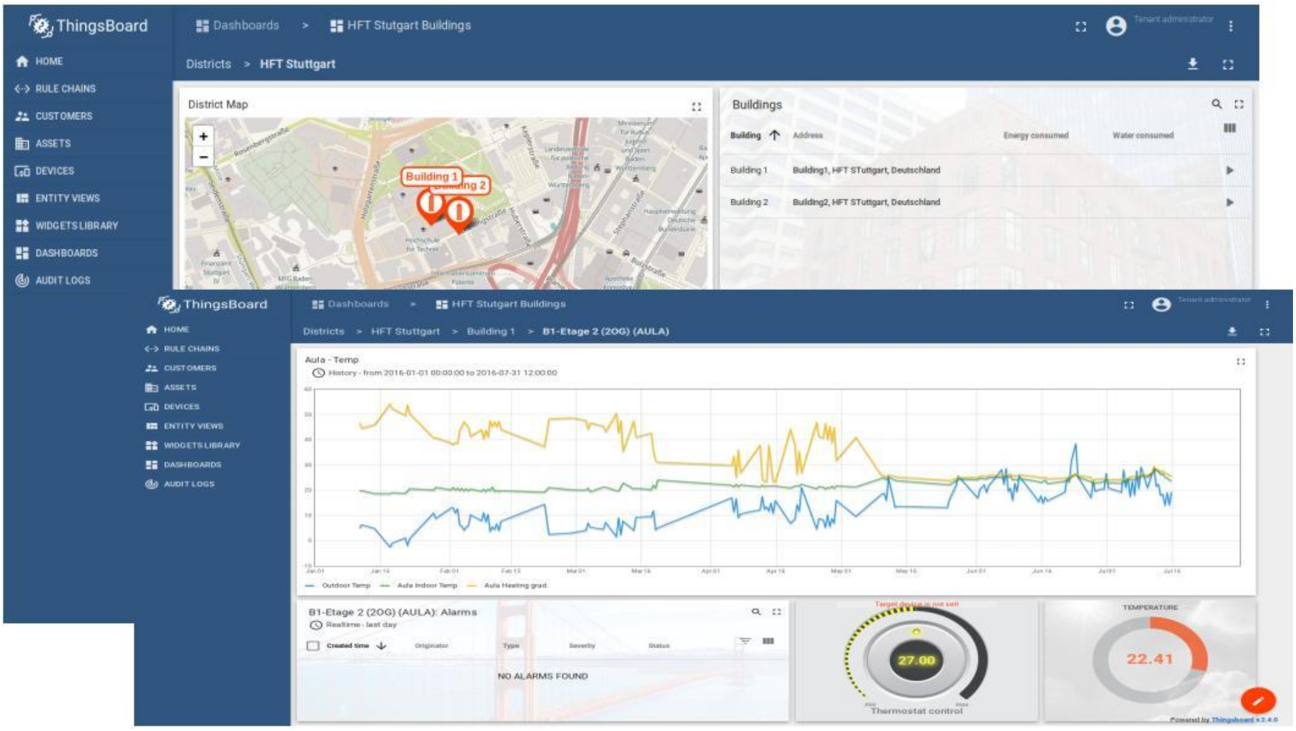

Fig. 2.To select a monitored workplace

4. Evaluation

In this section, Table[2] shows an example of the measured physical parameters describing the main parameters of environmental data in Aula, under two different exposure seasonal conditions.

For the developed evaluation phase, the Correlation and Linear Regression were chosen as the best choice for our analysis, – since the sample sizes of observed seasonal periods range from 9 to 200. Table[3] reveals the statistical function results. We aim to study the representation of environmental data performance by the mean of outdoor temperature.

Therefore, we went one step further and analyzed the P-Value and R-squared statistical functions. The P-value was less than 0,05 in all cases, the R-squared was great than 0 and close to 1, These results allow using the correlation and linear regression functions.

The calculated correlations value (see Table[3]) between the heating temperature and the outdoor temperature show that the values are less than 0 and too close to -1 (value as part 1 = -0.8349228, and part 2 = -0.8158783), thus we dedicated also that we have a strong negative linear relationship between the two measurements because their values are too close to -1. On the other hand, the correlation values between the indoor and outdoor temperatures in the two parts, are between 0 and 1, but near to 0. In this relation, we have a weak dependence between the indoor and outdoor temperature. However, this weak relation can not deny that the outdoor temperature can not represent the indoor temperature. This latter considered today as a hypothesis of real-time data analysis.

However, according to the statistical calculated values, between the outdoor temperature and the heating temperature,

it provides a linear relation. This relation allows the functional variation of the heating temperature according to the outdoor temperature change during the two periods. this relation is as follows:

$$Ht_1 = (-1{,}05156) \cdot Ot_1 + 51{,}11479 \quad (1)$$

$$Ht_2 = (-1{,}05156) \cdot Ot_2 + 51{,}11479 \quad (2)$$

Where Ht_1, and Ht_2 represent respectively the heating temperature at part 1 and 2 of the observed periods. Ot_1 , Ot_2 correspond to the outdoor temperature during the same observed periods.

The equations (1, 2) illustrate the linear relationship between outdoor and heating temperature, are tested to forecast heating temperature from outdoor temperature. The relationship developed here is dedicated to the presented research.

Table 3. Statistical results analyzing Aula's indoor and heating temperature by outdoor temperature in the cold Season in 2016.

Analyze Aula's (temp variation in 2016)	*Part 1 : Jan. 2016 til March 20116*		*Part 2 : Sep. 2016 til Dec. 2016*	
	Indoor Temp	*Heating Temp*	*Indoor Temp*	*Heating Temp*
Correlation	0.3710023	-0.8349228	0.3423	- 0.8158783
Estimated Values	19.71147	51.11479	20.31603	47.7064
Eff. Coeff. Out. Temp	0.09354	-1.05156	0.08871	-1.0614

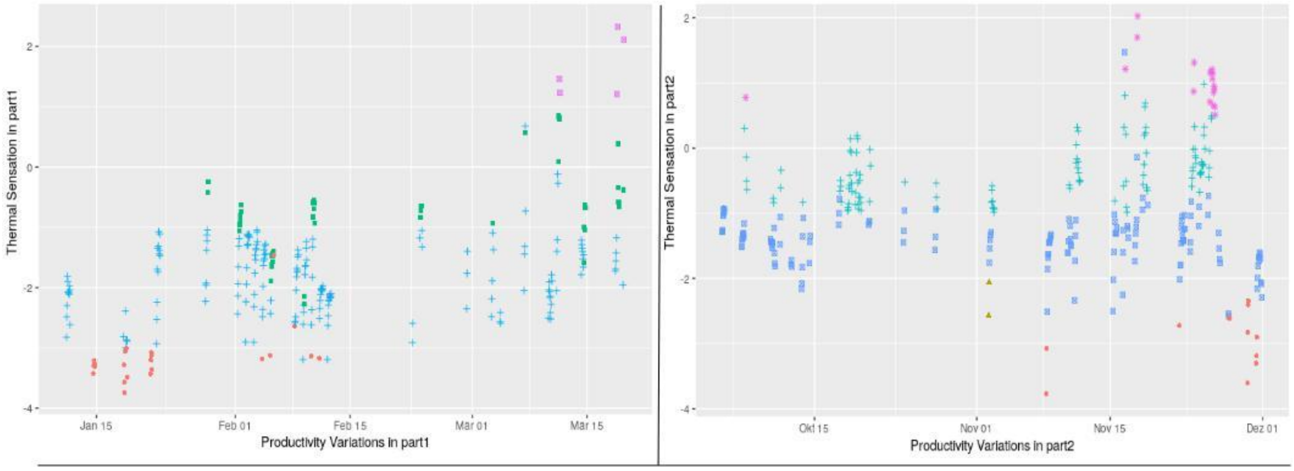

Fig. 3. Thermal sensation and occupants' productivity.

4.1. Use case:

Occupant performance analyze The work performance of occupants' productivity at work is one of our requirements to attend from the developed tool. Authors in [1, 2] show that it has previously been established that indoor environmental quality influences occupants' performance: a performance increases of as much as 10% or more can be expected following improvements of the indoor environment. The indoor ambient is strongly related to productivity [7]. However, metrics to evaluate the effectiveness of changes in occupants' productivity need communication (e.g., demand, response, etc.) with workers, because the provisioning of one single metric to present the humans' productivity does not seem realistic. On the other hand, many other factors like the workers' clothing, physical activity, metabolic, health, and adding the environmental parameters like indoor temperature, mean radiant temperature, air velocity and air humidity, etc. make part of factors' list that need to be taken in consideration. However, since all possible factors may vary in time and depend on different situations of workers, we decided to base our standard of occupants performance productivity, in this study, on the ASHRAE Standard 55, like in [2, 3, 8, 9, 10]. The ASHRAE determine a seven-point thermal scale (3= cold, -2 = cool, -1 = slightly cool, 0= neutral, 1= slightly warm, 2= warm, 3= hot). We integrated the ASHRAE protocol in our developed tool. Basing on this integration, we evaluated the thermal sensation in Aula during 2016.

Fig. 1 presents the result of the launched experiment. It shows that the thermal sensation distributed between cool and slightly cool. The corresponding indoor temperature ranged between 21 °C and 19 °C. According to the results obtained in [3, 4, 5], Which it confirmed that the highest productivity performance is at a temperature of approximately around 22 °C, and the performance reduced to 91.1% at a temperature of 30 °C, we deduced that the subjects in Aula in 2016 were in the ideal environment, which it indicates the efficiency of the evaluation of thermal sensation by the developed tool and confirmed our demonstration.

5. Conclusion

The correlation and regression analysis of the environmental data used as a function of the daily average outdoor

temperature was performed for the Aula's Hall of HFT Stuttgart University (Germany) in the cold season 2016.
Collected data were preliminarily filtered to consider only working days and only during the heating phase. A relationship was deduced to improve productivity and the effect of the outdoor temperature on space heating in the next years. Beyond the model predictive capacity, which is not the objective of this study, the value of these parameters confirms that the proposed system is indeed able to explain the before mentioned effect.

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