Interactive GUI for enhancing user awareness applying IoT-sensors and physics-assisted AI

Dietmar Siegele [a], *Paola* Penna [a], *Alice* Schweigkofler [a], *Orjola* Braholli [a], *Michael* Riedl [a], *Dominik T.* Matt [a,b]

[a] Fraunhofer Italia, Bolzano, Italy, dietmar.siegele@fraunhofer.it

[b] Free University of Bolzano, Bolzano, Italy

Abstract. Several studies proved that occupant behaviour has a significant impact on energy consumption and indoor comfort. Thus, monitoring data and Internet of Things solutions are used to address behavioural changes for promoting energy efficiency and increasing, at the same time, the comfort perception. The possibility of seeing invisible information, such as energy consumption or comfort parameters, on a digital support have been proved to be effective in increasing users' awareness and to encourage efficient behaviours. This paper presents a GUI developed for increasing the user awareness and involving them actively in addressing their actions and presents the back-end architecture for making prediction and sharing feedbacks with the users. By means of the interface user can: (1) Visualize information related to monitoring data, selecting, and filtering the data they would like to see. (2) Receive real time personalized feedbacks based on behavioural predictions defined by using Artificial Intelligence (AI) algorithm. The AI algorithms are based on a physics-assisted approach to achieve better results with less input. Missing (monitoring) data is calculated by applying physical models (building energy simulations) and only for the remaining parts machine learning models are used. Mainly we apply LSTM models. (3) Express personal comfort feedbacks based on comfort perception, for setting user-oriented feedbacks. The first part of the paper describes the architecture of the monitoring systems and presents the GUIs developed for two different case studies: a social housing building and a nursery school. The personalization of the GUIs based on user's typology has been done for enhancing the active participation and the involvement of the users in the project. The second part of the paper presents the back-end architecture of the GUI and the AI algorithms used for monitoring data analysis. The physis-assisted algorithm allows us to make predictions based on occupancy behaviour and to provide each occupant with tailored personalized feedback to promote energy-saving behaviours in real-time. We have placed more than 150 sensors in these two buildings that return us almost 1000 measured variables that can be used for the training of the AI models.

Keywords. IoT data, physics-assisted AI, health and comfort monitoring, user behaviour.
DOI: https://doi.org/10.34641/clima.2022.403

1. Introduction

Monitoring data and IoT solutions seems to be a promising strategy for driving the people's habits in taking effective actions for reducing the energy consumptions and, at the same time, increasing the indoor comfort perception of the users. Data from the Internet of Things (IoT) can be used by two main approaches:

- directly to optimize the control of the HVAC (Heating, Ventilation and Air Conditioning) systems and reducing the energy peak and the overall consumptions [1], and
- indirectly by communicating the monitoring data to the users in order to raise their awareness for adopting an energy efficient behaviour.

The development of user interfaces for communicating with users is highly investigated in recent literature [1]–[4] and by several European projects (The4Bees, EnerGAware, Klimakit, Sinfonia, OrbEEt, Entropy, GreenPlay). The studies proved that increasing the users' awareness, showing them information related to their energy consumption and sending them targeted feedback, can reduce the energy consumption by 15% to 25% [3]. The information can be shown by simple dashboards or more effectively by advanced digital tools [5], [6] that allows an interactive communication with users and a customization of the data visualization. [7]–[9] highlight which are the most important aspects that should be considered for developing an effective communications tool. They stated that a key role is played by the way in which the information is presented to the users. Some of the main aspects that should be considered and integrated for the development of an effective digital interface are:

- Real time feedback on the actions that the user should adopt.

- Benchmark of virtuous users in order to incentivise the competition and to increase the gaming effect.

- Visualization of real time energy consumption measurement and past data for allowing a direct comparison of historical and current situation.

According to [10] and [11] receiving daily tips seems to be effective in reducing energy consumptions. [10] developed a mobile application where the users receive daily tips for reducing their electricity usage. [11] developed a more complex user interface based on gamification where the users receive tailored, interactive tips, information, and data-driven messages that can give users a clear view of how their actions impact on the amount of energy they waste and how they can improve their active participation. Moreover, the systems propose rewards for consumers by sending stimuli to change consumer behaviour. Moreover, [12] proved that the gamification is a good strategy for keeping the users motivated and involved in driving their behavioural changes. The work of [13] proposes an approach based on visualization of real time data based on dashboards, which to a large extent follow the idea of using dashboards in cars to inform drivers of the current state of their car. Another important aspect is stated by [14]. The authors highlight the importance of allowing the users to express their preference on their comfort perception, to actively consider their point of view and integrating this information in the heating system management.

This paper proposes the development of a digital interface that integrates all these aspects. The developed GUI allows to provide interactive and customized real time information, based on the users' profile. The backend of the system uses AI algorithms for analysing monitoring data and a physis-assisted algorithm allows to make predictions based on occupancy behaviour. It can provide each user with tailored personalized feedback for energy-saving and comfort recommendations in real-time. We developed two different interfaces for a residential and a non-residential building. Moreover, the software architecture is designed in a modular way and allows to adapt the interface according to the actual necessities. The AI algorithm is trained as a global model for each building type, and it is re-trained for each single unit by applying transfer learning using actual data.

2. Methodology

2.1 Case study

We chose two case studies to prove our approach: a residential and a non-residential building.

Fig. 1 shows a school building, that is used as a nursery school. With this non-residential building we want to show how our approach can be used in a comprehensive solution by applying it to the overall building and to all classrooms. At the same time each classroom is independent in the use of the application. In total we count ten classrooms with altogether five classes with alternating room use. Four classrooms are equipped with a mechanical ventilation system, which is not known to users. Huge parts of the building are not renovated and show a low quality of the building envelope. Due to this, and a high complexity of the heating system, energy consumption is not analysed in this case study.

Fig. 1 - School building.

Fig. 2 depicts a residential building. In the residential building two flats were chosen where we apply the application. With this case study we want to prove that the approach can also be used in small units like an apartment without the need to apply it to the overall building.

Fig. 2 - Residential building.

The residential building has a very high energy efficient standard and uses passive house components (U-value of walls lower than 0.15 W/m².K, of windows lower 0.85 W/m².K). However, there is no mechanical ventilation system installed.

2.2 Monitoring solution

Our approach depends on sensor data. Thus, a monitoring solution was developed and rolled out in the two case studies. Several IoT technologies are available on the market. However, only a small number has the capability to be power supplied by battery. This is essential in our case studies, as we want to install our system in an existing building structure. We think that our approach is mainly feasible in existing buildings and therefore a long battery runtime is essential. In practise this can be guaranteed only by applying one of the three communication protocols ZigBee, EnOcean or LoRaWAN.

We decided to go for LoRaWAN, as it shows two main advantages. First, it has the longest radio range of all protocols. The presented case studies are situated within a distance of 500 metres, and it is possible to gather the data with only one gateway (= device to collect the data and forward it to a server). We use two gateways to improve the battery lifetime of the sensors. This is also the second advantage of LoRaWAN: it uses a modern hardware and software architecture. Designed for security, it allows us to guarantee a fully encrypted data communication from sensor to database. Furthermore, we use features like adaptive data transfer rates, that improves the battery lifetime. We are gathering data each 10 minutes or when an event happens (like window opening). We expect a battery lifetime of almost 10 years for all devices, expect of the Ursalink AM102 that is equipped with an additional display. Here we expect 1 year of battery lifetime.

Fig. 3 and Tab. 1 show the sensors used in the case studies. In overall, almost 150 sensors are in use.

Fig. 3 - Sensors used in the case study, from left to right: Ursalink AM102, ELSYS DOOR, ELSYS ERS CO2, mcf88 Weather Station.

Tab. 1 - Used LoRaWAN sensors.

Manu-facturer	Name	Type
Ursalink	AM102	Temperature, humidity, CO_2, VOC, presence, display
ELSYS	ERS CO2	Temperature, humidity, CO_2, presence
ELSYS	ERS EYE	Temperature, humidity, presence, people detection
ELSYS	ERS DOOR	Opening/closing
mcf88	MCF-LWWS00	Weather station, temperature, humidity, global radiation, wind speed and direction, rain
MClimate	Vicki	Thermostatic valves

Fig. 4 shows the architecture of the monitoring solution. The sensors send the data wireless via LoRaWAN to a LoRaWAN server. A gateway is used as a physical device to forward the (encrypted) sensor data from LoRaWAN to WAN (internet). The gateways are connected to the LoRaWAN server via VPN and a cellular connection. As LoRaWAN server LORIOT is used.

On the LoRaWAN server sensor data is decrypted and is forwarded via encrypted MQTT to a timeseries database. Here we use InfluxDB as a database, but the design allows the use of any timeseries-based database. Data is then accessible by the application for further use (see next section).

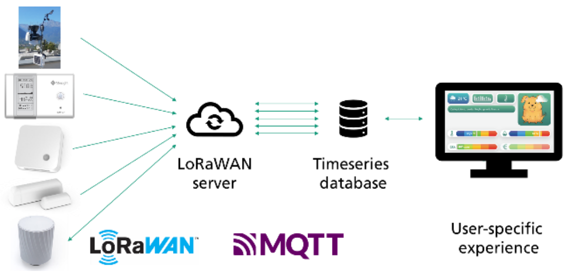

Fig. 4 - Architecture monitoring system.

2.3 Software architecture of the application

Fig. 5 depicts the (simplified) software architecture of the application. The application is based on web technology, namely HTML, CSS and JavaScript for the frontend, ASP.NET for the backend and Python for the micro services. Frontend, backend and micro services are separated from each other and are connected via a RESTful API. A full user authentication (from frontend, over backend to micro services) is implemented. That guarantees full data integrity. A sensor management is implemented by gathering data from the LORIOT LoRaWAN server by applying a RESTful API. The frontend (GUI) can be changed by applying different themes. AI-based recommendations and the handling of user feedback are implemented by micro services based on Python. A specially developed AI-hub ensures the data exchange between micro services and backend. The application is multi-language compatible and at the moment English, German and Italian are implemented as languages.

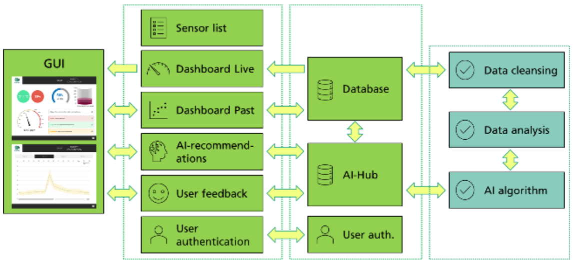

Fig. 5 - Software architecture.

The GUI itself was developed within a design thinking process. Fig. 6 depicts the results of the "ideate" part (prior step of rapid prototyping) of the GUI for the school building. Using the presented software architecture, specific themes can be developed and easily implemented.

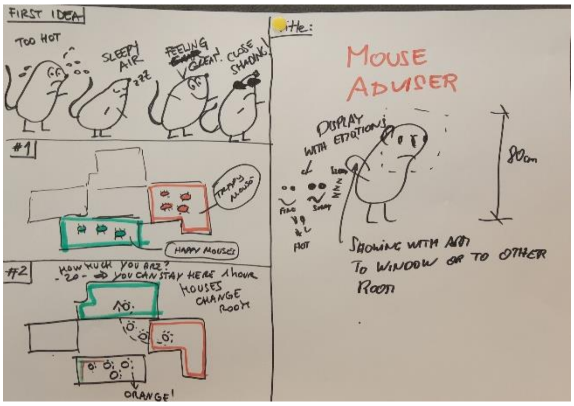

Fig. 6 - Design thinking process of the GUI (here for the school).

Within the design think process also possible advices for the users were developed. In total 64 different recommendations were rolled out in the first version of the application. Typical suggestions have a format similar to "The air quality here is not very good. But outside it is very hot, so let's wait a little bit before opening the windows.". The following categories for giving advices on the comfort are implemented in the first version: temperature, humidity, indoor air quality and illuminance.

2.4 AI-algorithm

We use two AI-algorithms that were implemented as Python micro services. The first AI algorithm is a classification tree that decides, either depending on actual real time monitoring data or on predicted data, if a recommendation (see section above) is useful for a user. The second algorithm is based on a long short-term memory (LSTM) time series forecasting and predicts the room states (temperature, humidity, CO_2, illuminance) in 15, 30, 45 and 60 minutes. This allows us to give advices already in advance. The prediction uses a semi-physical approach to achieve a higher accuracy of the LSTM network with less training data. The results of this predictions are again the input data for the beforementioned classification tree. If no advice based on the real time data is found (i.e., the comfort is optimal), recommendations for future conditions, based on the prediction can be displayed in the application.

The classification tree is generated by applying decision tree models from the *scikit-learn* toolbox. Training data is generated from measurement data and by manual labelling. As input data, data from Tab. 2 is used (same data as for the neural network, see below). As labels, the advices as described in the section above are used.

For the timeseries forecast a recurrent neural network (RNN) using the so-called LSTM architecture is implemented [15]. For each room (classroom) or each apartment an own model is used. However, all models use the same input and output vectors. This allows us to train once a model of a single room or apartment and then to apply transfer learning for other rooms. By this, we achieve faster training results, and, in the future, we will be able to use a shorter training period for similar building structures.

Our model uses 256 nodes that are based on LSTM with a forget gate. We use a multi-output model, so that it is possible to predict the future room states but also the future weather conditions by one model. This implicates that we need a high number of nodes. For training we allow a maximum of 100 epochs. The model sees an input data length of 7 days. Retraining is carried out for all different rooms based on previous models to reduce the necessary time for training.

Tab. 2 shows the input data vector that is used for the neural network. Apart from measurement data we also use physically calculated data for the solar radiation on the vertical surfaces (South, North, East, West), that is crucial for solar gains through the windows. The area of the windows is also introduced by using an accurate BIM (Building Information Modelling) model of the case studies. By applying data exchange via the file format gbXML this information is imported into the micro service that runs the neural network. In future we plan to implement even more sophisticated physical calculations based on building energy simulation, like air flow calculations.

Tab. 2 - Input data for the neural network.

Input data	Type
Hour of day as sine	Generated from timestamp
Hour of day as cosine	Generated from timestamp
Day of year as sine	Generated from timestamp
Day of year as cosine	Generated from timestamp
Day of week	Generated from timestamp
Hour of day	Generated from timestamp
Temperature	Measured value of temperature
Humidity	Measured value of humidity

CO_2	Measured value of CO_2
Pressure	Measured value of ambient absolute air pressure
Illumination	Measured value of illumination
Motion	Measured value of motion
Window South opening state	Measured opening state of South windows (summed up)
Window North opening state	Measured opening state of North windows (summed up)
Window East opening state	Measured opening state of East windows (summed up)
Window West opening state	Measured opening state of West windows (summed up)
Door opening state	Measured opening state of door against corridor
Ambient temperature	Measured ambient air temperature (weather station)
Ambient humidity	Measured ambient air humidity (weather station)
Ambient pressure	Measured ambient air pressure (weather station)
Wind speed x-direction	Measured wind speed (weather station)
Wind speed y-direction	Measured wind speed (weather station)
Solar radiation South orientation	Calculated solar radiation on vertical surface against South based on measured global radiation
Solar radiation North orientation	Calculated solar radiation on vertical surface against North based on measured global radiation
Solar radiation East orientation	Calculated solar radiation on vertical surface against East based on measured global radiation
Solar radiation West orientation	Calculated solar radiation on vertical surface against West based on measured global radiation
Window South area	Area of South windows (summed up)
Window North area	Area of North windows (summed up)
Window East area	Area of East windows (summed up)
Window West area	Area of West windows (summed up)

3. Results and Discussion

3.1 Graphical user interface

Two different graphical user interfaces (GUI) were developed for the case studies. Fig. 7 and 8 show the GUI for the school building. The teachers and the children can change the room where they are, in every moment (Fig. 8). All main rooms are equipped with tablets, that have installed the application. To simplify the use of the app for the children, almost no text was used on the main pages. Only when asking for the advice (here not visible), the textual advice will be accompanied with a picture of the action that the mouse should do (compare Fig. 9).

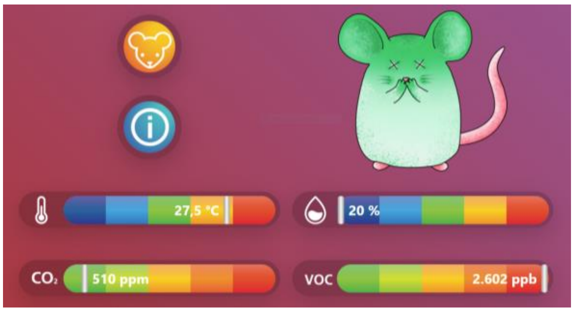

Fig. 7 - GUI of school building (adviser).

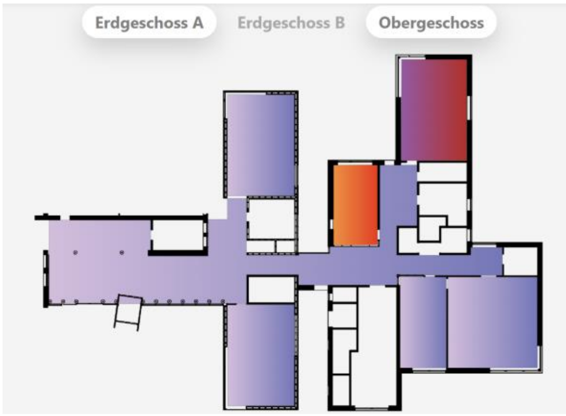

Fig. 8 - GUI of school building: room selection.

Fig. 9 - GUI of school building: different states & actions.

Fig. 10 shows the GUI used in the residential building. The occupant can see actual data of a central sensor, past data of sensors in each room, actual weather and the advices how to improve the IAQ and to reduce the energy consumption.

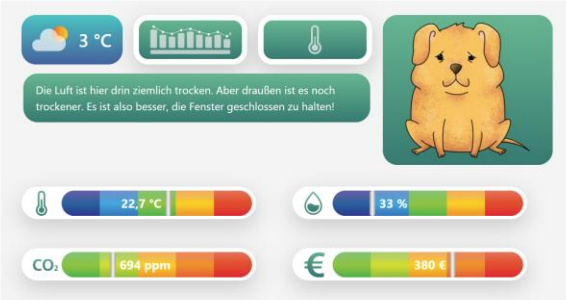

Fig. 10 - GUI of residential building.

In both GUIs the optimal temperature and humidity range is determined depending on the thermal comfort, mainly on the concept of predictive mean vote (PMV). The user has also the possibility to change the setpoint of the thermostatic valves in each room. Also this is realized by LoRaWAN and LoRaWAN compatible thermostatic valves.

3.2 AI-algorithm

Training of the decision tree was carried out by using the period between 2021/09/27 and 2021/10/31. The labelling was carried out for the whole period by applying a semi-automatic labelling routine. The advices described in the section above were used as labels and in addition a label for an "all okay" state. The first three weeks were used for training and the last two weeks for validation. In overall a prediction accuracy of around 90% was achieved.

The main advantage of this approach is that the overall decision tree does not have to be programmed. Programming a decision tree, considering room sensor data and weather information, as input and (at the moment) 64 different results leads to a very high effort in programming and a high number of errors can be introduced. Considering the actual result of 90% accuracy of prediction of the decision tree, in overall better results can be expected compared to traditional approaches. Further, when more data is available a re-training can be carried out. Also adding additional advices is very simple by applying this approach. However, the labelling takes quite a lot of time and needs expertise. It is not a trivial work and is at the same time very time-consuming. Moreover, due to the very time-limited training period (limited in particular to a specific season), not all available labels could be used. This means, that more time periods are necessary to ensure that all labels can be used and to achieve an even higher prediction accuracy.

Training of the RNN was carried out by using the period between 2021/09/27 and 2021/12/19. Here 70% of the data was used as training data, the rest as validation data. The batch size was data of 12 hours. We take a 10-minute interval for the data points. The prediction is carried out for 15, 30, 45 and 60 minutes. We train a model for each single room; however, we use the previously trained model as starting point. With this approach, we need for the further rooms only about 3 epochs to get a high accuracy. In overall, the accuracy of the prediction is very high. There is only a very little amount of time, where the prediction fails completely (< 1%). As quality criteria for failing of the prediction we set for the indoor temperature a range of 0,3 °C, for the humidity 3%, for the illumination 10 lux and for the CO_2 concentration 50 ppm. Highest failure rate can be seen in the illumination.

3.3 Preliminary monitoring results

We present here first preliminary monitoring results of the application impact. At the moment it is only feasible to evaluate the comfort parameters, as changes there can already be obtained after a very short time. For evaluating the impact of the advices that could reduce the energy consumption, a longer observation period is necessary.

For the indoor air quality in particular the CO_2 concentration was analysed. The period between 2021/10/04 and 2021/10/24 was taken for the reference values. The validation period of the application is between 2021/12/06 and 2021/12/19. Tab. 3 shows the number of total hours in the two weeks periods with CO_2 concentrations above 800 ppm for the school building. The use of the classrooms was in both periods the same. Also the number of children was unchanged. Independent of this study, teachers have been advised to open the windows regularly due to the COVID pandemic in both periods. In the validation period the ambient temperature was significantly lower than in the reference period (which usually leads to a reduced ventilation). The total hour of use in these periods is each about 70 hours.

Tab. 3 - Hours with CO_2 concentration above 800 ppm.

Room	Reference	Validation	Difference
G01a	16.83 h	2.17 h	-87%
G01b	16.17 h	11.50 h	-29%
G02a	4.33 h	3.83 h	-12%
G02b	35.33 h	51.33 h	+45%
G03a*	5.67 h	0.00 h	-100%
G03b*	4.17 h	3.83 h	-8%
G04a	8.17 h	10.83 h	+33%
G04b*	11.0 h	22.50 h	+105%
G05a*	1.00 h	0.00 h	-100%
G05b	4.25 h	3.17 h	-25%
TOTAL	**106.92 h**	**109.16 h**	**2%**

** Equipped with mechanical ventilation system.*

For the classrooms the hours of CO_2 concentration could only be reduced by 2%. For the residential building we can obtain the same results in our first analysis. In terms of thermal comfort, no significant change was obtained so far, but the observation period is rather short for such analysis.

4. Conclusions and Outlook

We conclude that with a high number of sensor data available creating AI models is a relatively simple task. The decision tree approach allows to reduce the demand of necessary work to implement decision logics considerably. However, the labelling task is time-consuming and non-trivial. Here more sophisticated approaches are necessary to automate the labelling. Non-supervised machine learning models were not considered in this work. However, for decision trees they are not common, since the data is not labelled, there is no objective function to determine an optimum clustering. A prior unsupervised clustering of the data would be possible to reduce the amount of necessary labelling.

Short-time prediction by applying RNNs and the LSTM approach seems to be very convenient. In particular when combining it with physical calculated data, training time and prediction results can be improved. It seems that it can help to find the neural network more direct correlations in a shorter period of time. However, for training a significant amount of data is necessary to achieve good results. Combining it in a second step with the decision tree model seems to be convenient.

According to preliminary results the impact of the application in terms of indoor air quality seems to be modest. However, for a comprehensive validation a longer observation time is necessary. Also for evaluating the aspects linked to energy demand a longer observation time is needed. Therefore, the monitoring will be continued for the next months to gather data of an overall heating seasons. Comparison with energy demand data of previous heating seasons will be carried out.

5. Data Access Statement

The datasets generated during and/or analysed during the current study are not available because the project is still ongoing and results are preliminary, but the authors will make every reasonable effort to publish them in near future.

6. Acknowledgement

The research leading to these results has received funding within the project SINCRO from the European Regional Development Fund (Fondo Europeo di Sviluppo Regionale FESR Alto Adige 2014-2020) under the Grant Agreement n. FESR1141 CUP B54E20002030001. The authors would like to thank the school building supervisors as well as the building users for their contribution and participation in this project.

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