Occupant Feedback and Context Awareness: On the Application of Building Information Modeling and Semantic Technologies for Improved Complaint Management in Commercial Buildings

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Abstract— Common methods for submitting hardware- or comfort-related complaints in an office or industrial environment, such as online forms or via a telephone hotline, can lead to misinterpretations of the issue and/or be perceived as being cumbersome by the submitter. This can act as a barrier for the submission of feedback and thus cause the facility management to remain unaware of unsatisfactory comfort conditions or faults, which can result in further issues and costs. In order to reduce the submission effort, a novel software-based solution is proposed, which automatically determines the most probable complaints, suggests them to the user and, when possible, automatically solves them. This is achieved by employing detailed context information stemming from a Building Information Model, the Building Automation System and past complaints submitted by the occupants. This information is integrated and represented with semantic technologies, which allow to formally organize the information and describe the relationships between the data. The solution was implemented as an app and was demonstrated in a real office environment. The reduced effort of submitting feedback via the app led to a strong increase in the submission of comfort-related complaints, showing the effectiveness of the proposed solution.

Keywords—semantic technologies, ontology, BIM, BAS, feedback, complaint management, context awareness, digital twin, smart building

I. Introduction

The rise of Building Information Modeling (BIM) does not only have the potential to revolutionize the planning of buildings and their technical systems, but also offers opportunities during the operational phase. In this paper, we present an approach that combines BIM, semantic technologies and Building Automation Systems (BAS) to improve the management of occupant complaints.

Commercial buildings, such as those employed for office or industrial purposes, must be continuously monitored in order to ensure occupant comfort and suitable conditions for manufacturing processes. In order to assess the current conditions in a building, facility managers typically rely on three main sources of information:

- Sensor measurements and, in some cases, the results of algorithms that analyze these measurements [1]
- Observations from routine maintenance inspections
- Feedback from occupants, factory workers, etc.

Relying on occupant feedback can be advantageous, because certain issues are difficult or too costly to measure, such as a very small leak, unusual vibrations in a machine or the thermal comfort of the occupants, among others. The latter is especially challenging, because it depends on myriad variables, such as the user's clothing and metabolic rate [2].

In order to address submitted complaints and issues effectively, facility managers require the information received from occupants to be *complete* and *accurate*. In practice, communication between facility managers and occupants often fails at transporting feedback that is both complete and accurate: for example, occupants may describe the problem incorrectly or fail to recognize or denominate their correct location within the building. Moreover, if the communication involves a high effort on any of the two sides, feedback may be ignored or not be communicated in the first place.

In this paper, we address the challenge of designing an application that enables occupants to submit complete and accurate feedback with a low effort. The solution approach is based on the automatic suggestion of the *most probable* complaint types, whereby the occupant can quickly find and select the relevant complaint type and submit individually tailored feedback. Moreover, if the technical systems in the building allow it, the complaint is solved automatically, thus reducing the effort for the facility management. Both the complaint suggestions and the automatic complaint solving rely on context awareness; in the course of this paper, we will explain why we consider BIM and semantic technologies to be ideally suited for this purpose. The suitability of this approach has been validated in an ongoing field test; the results presented here are based on the first five months.

II. Related Work

Several solutions exist that collect feedback from occupants to improve the operation, comfort and maintenance of buildings.

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Honeywell's Vector Occupant App provides indoor wayfinding, space reservation, access control, and basic comfort feedback functionality [1]. The user can indicate thermal comfort issues by employing two simple buttons in the app: "Too warm" and "Too cold". Besides, faults can be reported to facility management, but only as human-readable text. Similarly, the 75F Occupant App, as a part of a control and monitoring solution for light commercial buildings, allows for collecting occupant feedback in a textual form [4]. Both solutions focus on informing facility managers and helping them act upon the feedback, improve comfort or initiate repairs.

Other solutions focus on providing optimized thermal comfort for spaces with several occupants, which is a very challenging problem due to the individual comfort requirements [5]. This can be handled by clustering occupants into different groups with similar comfort requirements, and assigning them to zones that best match their needs ([6], [7]). In the case of [7], the solution constitutes a comfort management system that also tries to adapt comfort in the spaces and zones by optimizing the particular control strategy. There are several other solutions that also aim at finding the best control strategy for spaces occupied by people with different comfort requirements: In [6], neural networks are used for predicting acceptable temperature setpoint values[8], whereas in [7] machine learning is applied to learn preferences for a zone[9]. The research-based proof of concept "Building Energy Efficiency Solutions" (BEES) also collects occupant feedback and solves the collaborative temperature control problem as a convex optimization question [10]. Finally, in [9] fuzzy rules are employed for solving that problem [11].

What is similar for all mentioned solutions is that their primary concern is comfort (but not faults), that they support just a few feedback types (e.g. "too warm", "too cold") or take plain text only, and that they do not use BIM or just floor plans as a simplified building model. Most importantly, and to the best of the authors' knowledge, currently no solution exists that predicts the most likely complaint type. The solution we present in this paper is distinct from the available solutions in the following points: a) It provides an extensive set of predefined comfort- and fault-related feedback types, which are organized and categorized in an ontology; b) It uses a fully-fledged BIM of the building, from which it derives a knowledge graph that constitutes the semantic model of the building, occupants and feedback; c) It implements a knowledge-based approach and applies rules, e.g. to reason about issues possible at a location; d) It predicts the most likely complaint types.

In the following sections, our novel solution and its advantages will be explained in more detail.

III. Automatic Complaint Suggestions Based on Context Awareness

The different types of complaints a building occupant may have is broad, ranging from comfort topics (e.g. too warm, too dry, too dark) to hardware-related complaints (e.g. a leaking tap, unusual machine vibrations, a burnt light bulb). When using software-based systems to submit a complaint, it is often difficult and time consuming to find a suitable complaint type amongst the multitude of options. In the case that there are no (matching) predefined complaint types, users have to provide a plain textual description, which can lead to misinterpretations on the facility managers' side. The main solution approach presented in this paper is the automatic prediction of the complaints that are most relevant to the user, with the objective of reducing the complaint submission effort.

The main mechanism employed to select the most probable complaints is the explicit consideration of context information. This information includes, but is in principle not limited to, the following:

1. Location: Where the occupant is located in the building.
2. Building geometry: The distribution of rooms and other spaces in the building.
3. Usage information: The planned usage of rooms and spaces in the building (e.g. office, conference room, reception, toilet, storage, kitchen).
4. Topology and characteristics of the building's technical systems (e.g. lighting, HVAC, fire protection, sensors).
5. Current and past device readings (e.g. sensor and actuator values) from the BAS.
6. Complaints of other occupants at that location or other locations close by.
7. Previous complaints of the occupant.

The predicted complaint types are then prioritized and displayed to the occupant as suggestions, which allows him/her to select the relevant complaint type(s) and submit them. In the following sections, we present how this context information is employed in the selection of the most probable complaints.

A. Selection of Relevant Complaints

The first step towards predicting the most probable complaint types is to identify *possible* or *relevant* complaint types, based on the data mentioned in points 1-4 in the list above. If the occupant's surroundings contain certain elements, complaint types related to these elements will be selected for the following steps. Analogously, if the surroundings lack certain elements, it is improbable that the occupant will want to complain about them, and thus these complaint types are not considered further. Two illustrative examples are given in Fig. 1.

`IF` *`location`* `is a` *`toilet`*`,` **`THEN`** *`toilet-`*`related complaints are relevant` (e.g. a leaking tap or a defective urinal)

`IF` *`location`* `has` *`walls`* `with` *`windows`* `in it,` **`THEN`** *`complaints`* `related to` *`blinds`* `and` *`shading`* `are relevant.`

Fig. 1. Examples showing the selection of relevant or possible complaints at a certain location

By doing this, the potentially very long list of all complaint types is reduced to the possible types at that particular location only.

B. *Refinement of Suggestions with Measured Data*

Once the possible complaint types have been identified, they are further refined in a second step in which the *most probable* complaint types are predicted. This is achieved by combining the context information described in the previous step with data from the BAS (point 5), complaints submitted by other users (point 6), and previous complaints of the user (point 7). Whenever there is data from the BAS involved, we call it *reading-based predictions* in the following. In this case, available device readings at the specified location in the building (e.g. sensor and actuator values) are correlated with the probability of a certain complaint type. Two main methods were considered in this case:

1. Rule-based: Predefined rules, which use the device readings as an input, decide whether a complaint type is probable or not. For example, if the measured air temperature at the occupant's location is high, it is probable that he/she will complain that it is too hot.
2. Machine learning / pattern recognition: In principle, past readings and occupant complaints can be statistically correlated in order to predict whether a certain complaint type is probable or not. For example, if a certain occupant typically complains that it is too hot above a certain temperature, this complaint type will be predicted as being probable when the temperature reaches a similarly high level.

Although the application of machine learning methods to the multi-variable problem of individual comfort is a very promising approach, in practice it became evident that the amount of submitted complaints required to generate accurate models of the occupants' preferences requires a long period of data collection. For example, in [12] the occupants had to submit an average of over 60 responses in order to achieve a stable prediction with machine learning models. Several occupants never crossed this threshold during the three-month field test, because they did not submit responses regularly enough. In contrast, simple rule-based systems work robustly even with small amounts of data and can be improved over time. Therefore, a machine learning-based approach was discarded in favor of rule-based predictions in order to provide meaningful suggestions to the users during the complete field test period. The use of machine learning on large amounts of collected complaint data is a topic of future research.

In the developed solution, reading-based predictions are mainly applied to comfort-related complaint types, such as:

- Too hot/cold: Based on temperature measurements
- Too dry/humid: Based on relative humidity measurements
- Too bright/dark: Based on illuminance measurements from presence detectors
- Poor air quality: Based on CO_2 measurements

In the case that no (relevant) device readings are available, complaints submitted by other occupants are used as a basis for the suggestions. For example, it is assumed that if an occupant at the same location or one nearby has complained about something, such as a leaking tap, it is more probable that other occupants will also want to complain about that specific problem instead of something else. This procedure to determine the suggestions is especially relevant for hardware-related complaints, such as the mentioned leaking tap, because the sensors required to detect them automatically are usually not available in the building.

C. *Advanced Integration of BIM and BAS for Complaint Prediction*

Of special interest is the integration of detailed geometric information in the BIM with measurements from the BAS for complaint prediction, including the geometry of the building's space layout and technical systems. In the following, we exemplify this with complaints regarding the external shading system.

Consider an office space with glazed façades and an external shading system. The shading system is controlled via the BAS, which sets the position of the blinds and the angle of the slats depending on the time of day and the direct solar irradiation, which is measured on the roof of the building. The occupants can also manually override the position and angle with a button located close to the particular blinds. After a manual override, the position and angle stay fixed for a certain period of time, after which the shading control returns to the automatic operation mode.

During the day, occupants in the building may become unsatisfied with the shading system, either because the automatic settings or the manual override lead to direct sunlight reaching the occupants' eyes, computer screens, etc. For the sake of argument, assume that a dissatisfied occupant sitting in an open plan office wants to change the position of the blinds or angle of the slats, but standing up and walking to the blind in question is too cumbersome. Instead, the occupant decides to employ the solution presented in this paper to submit a "`too bright`" complaint.

Based on the procedure described previously in this section, complaint types regarding the blinds and the brightness within the office space are selected as *possible* complaints types, because the open plan office is surrounded by windows with an external shading system. In a second step, the solution calculates whether a "`too bright`" or "`blinds should be down`" complaint type is *probable*. Employing the detailed geometric information in the BIM, which in this case includes the external shading elements, the relevant blind(s) for the location of the occupant are determined. Specifically, the sun's current position, the coordinates of the occupant's location within the building and the exact dimensions, coordinates and corresponding façade orientations of the blinds are required. With this information, the procedure to determine the relevant blind(s) is as follows:

1. In a first step, all the maximum azimuth angles α between every location and the end of every blind (iterating clockwise from the north) is calculated (see Fig. 2).
2. Once the maximum azimuth angles for the analyzed location are known, the formula $\alpha_n > \beta$ is checked

clockwise from the north, where β is the current azimuth of the sun and n is the number of the blind.

3. The first blind for which $\alpha_n > \beta$ is true is selected as the relevant blind, because it is the one with the potential to cast a shadow over the analyzed location.
4. In order to increase the robustness of the solution against inaccuracies and occasional movements of people at their desks, a second relevance check is applied: $\alpha_n + \Delta > \beta$, where Δ is a tolerance angle. In other words, the first blind (if any) for which $\alpha_n + \Delta > \beta$ is also considered to be relevant.

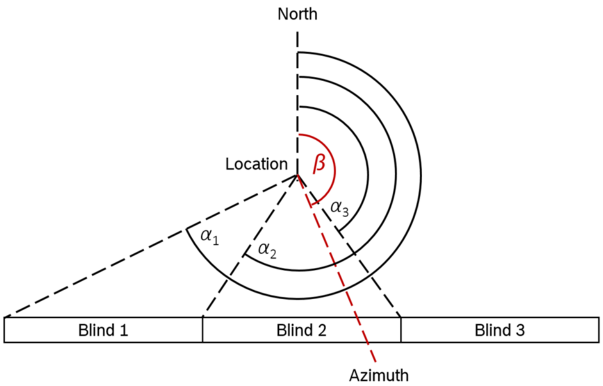

Fig. 2. Identification of the relevant blinds for a particular location within the building using detailed geometric information from the BIM

To exemplify this, assume that $\alpha_1 = 250°$, $\alpha_2 = 200°$, $\alpha_3 = 160°$, $\beta = 170°$ and $\Delta = 20°$. Applying the previous steps, it becomes evident that blind 2 is the relevant blind, because this is the first blind for which $\alpha_n > \beta$. However, the sun's azimuth is very close in value to α_3, which means that e.g. a small back-and-forth movement of the occupant in his chair may cause him to get direct sunlight in his eyes. As $\alpha_3 + \Delta = 180°$ and thus $\alpha_n + \Delta > \beta$ is true for blind 3, it is also considered to be a relevant blind. Once the analysis for the azimuth is completed, an analogous procedure is applied for the zenith angle of the sun and the dimensions of the windows, determining whether the sunlight can reach the analyzed location or if it is blocked by the façade.

Once the relevant blind(s) have been identified solely from the geometry of the building, the location of the occupant and the sun's current position, information from the BAS is employed to verify whether a complaint regarding the selected blind(s) is probable. This information includes the measured magnitude of the direct solar irradiation and the setpoint or state of the blind position and the angle of the slats. If the direct solar radiation is higher than a certain threshold and the selected blinds are open, the probability of the occupant wanting to complain about it being "`too bright`" or that the "`blinds should be down`" is high. Based on the described analysis, these complaint types are then selected as being probable and are presented to the occupant as complaint suggestions.

D. Automatic Handling of Complaints

Rich, machine-interpretable context information is not only useful when determining the most probable complaint types: If the relevant actuator setpoints can be modified in the BAS, the complaints can also be handled automatically. This can be illustrated with the external shading example presented previously: If the occupant selects the suggested "`too bright`" complaint, the position of the relevant blinds can be automatically set to "`fully closed`" and/or the angle of the slats can be closed further, while all other blinds are unaffected.

Analogously, myriad state and actuator setpoints can be automatically modified to respond to the occupants' complaints about temperature, humidity, air quality, noise levels due to the ventilation system, etc. By taking advantage of the rich context information, correlating an occupant's complaint with the corresponding controller or actuator can be done solely in a software-based manner, without requiring a dedicated HMI (Human-Machine Interface) for each controller or actuator, as is the case with room-based thermostats or buttons to control individual blinds.

IV. Smart Feedback Application

In order to realize the automatic complaint suggestion concept (Section III) in real office environments, a dedicated software solution was developed. The "smart feedback" application is implemented as a *Progressive Web App* (PWA), which allows users to submit feedback from different devices, such as smartphones, tablets and desktop computers (Fig. 3). The user can open the app by directly following a link or by scanning one of many QR codes distributed over the area. These codes include not only the URL of the app, but also a unique ID to allow localizing the user. Alternatively, it is also possible to set and change the location of the user within the app. In principle, other indoor localization techniques, such as WLAN- or Bluetooth-based solutions, can also be employed. The app communicates to the backend via an exposed REST API.

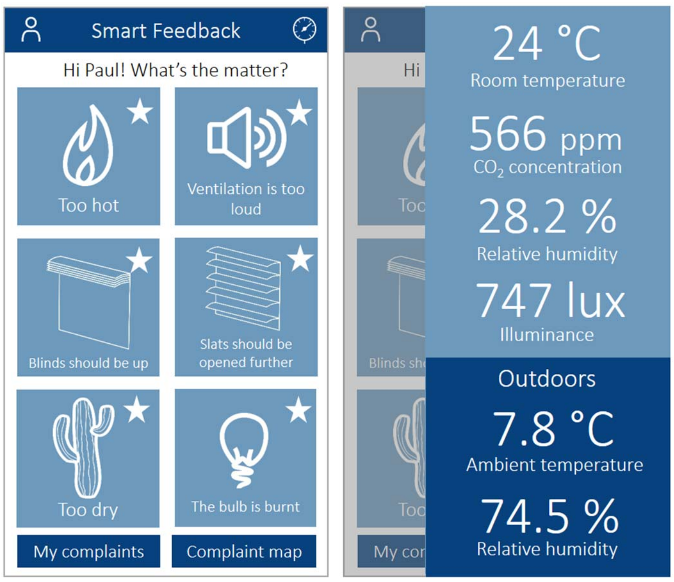

Fig. 3. Suggestions (starred) and the sensor values that triggered them

If a user has already authenticated during a previous session, he/she is immediately directed to the main page of the application depicted on the left side of Fig. 3. It consists of the most probable complaint types first, followed by different complaint type clusters like all comfort-related constraints (not visible here, cf. taxonomy in Fig. 6). By clicking the icon on the upper right, a list of current measurements is presented, as can be seen in the right side of Fig. 3.

When the user clicks on a complaint type, the backend decides if the complaint can either be solved by the system itself (like adjusting a suitable setpoint), or a ticket in the facility management system should be created, enriched with additional meta-data like the user's location and comments. This workflow is depicted in Fig. 4.

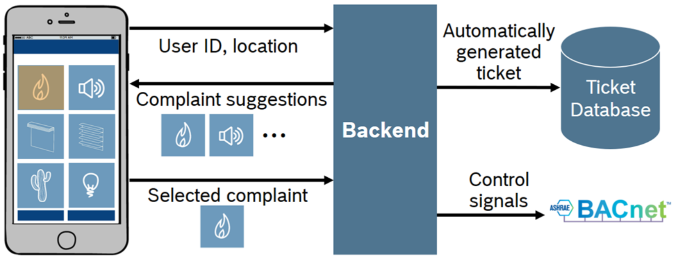

Fig. 4. Illustration of the working principle

If a user wants to create a complaint in a specific location where a similar complaint has already been reported, the system asks the user if he/she would rather vote for the existing complaint instead of creating a new one. Based on the votes, it is possible to achieve a prioritization of complaints, which may be beneficial for the facility management to identify the occupants' most urgent complaints. Furthermore, it is also possible for a user to see a map of the current floor with all active complaints in each location (see Fig. 5) and also to vote for them this way.

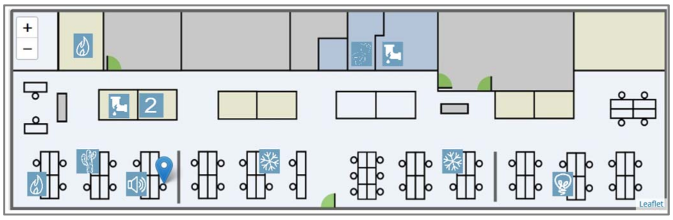

Fig. 5. Complaint map in the web app

V. SEMANTIC MODEL

A core element of this solution is a detailed *semantic model* of the buildings and their technical systems, and of the occupants and their complaints. *Semantic technologies*, and in particular the formal ontology language OWL (Web Ontology Language), provide appropriate means for defining machine-interpretable and –processable semantic models. A semantic model, also called a *knowledge graph*, typically consists of two parts:

1. The *ontology*, comprising:
   a. Definition of classes, properties and relations that are relevant for a domain
   b. Constraints, axioms and rules that formalize the laws and expert knowledge in a domain
2. An *instance model*, comprising instances of classes, their specific property values and relations to other instances.

For our solution, we developed a *domain ontology* that provides the vocabulary for modeling buildings and feedback. The ontology defines classes, such as `Site`, `Building`, `Space`, `Device`, `Person`, `Feedback`, `Complaint` etc.; properties such as `name`, `date`, `comment`, `description` etc.; relations such as `hasLocation`, `contains`, `wasAttributedTo`, `supplies`, `is-LocatedAt` etc.

The `Feedback` class in the ontology is the entry point (i.e. superclass) for an extensive set of predefined comfort- and fault-related feedback types, which are defined in a class hierarchy or taxonomy. An excerpt of the class hierarchy is shown in Fig. 6. All these feedback types are supported by the app and can be selected by the occupants.

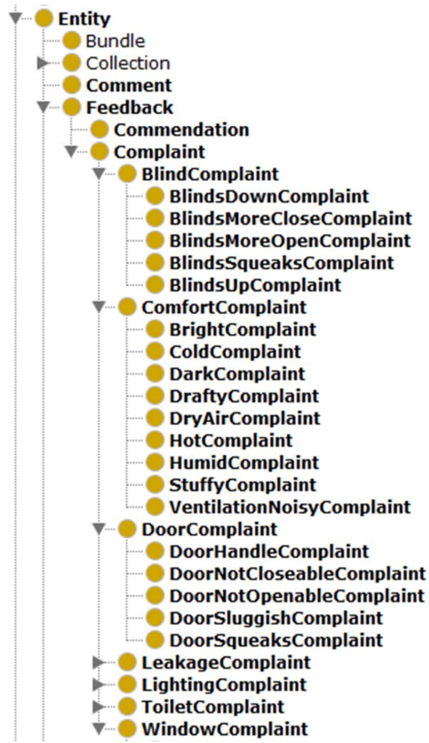

Fig. 6. Taxonomy of feedback type classes defined in the ontology

An *instance model* uses the ontology vocabulary and represents a detailed model of a specific building, i.e. it describes a building with all its entities and properties relevant for the complaint management. The instance models can comprise information about the following:

1. Building:
   a. Hierarchical containment structure, e.g. `Site contains Building contains Floor contains Space`, and related properties, e.g. area, volume, adjacency
   b. Geographical location, i.e. climate zone, altitude, orientation of facades and windows
   c. Room types, e.g. office space, kitchen, server room, restroom, stairway

d. HVAC system, including its assets and topology (e.g. Chiller `supplies` Air Handling Unit `supplies` Volume Flow Controllers `supplies` Air Terminals), devices (e.g. sensors, controllers, actuators), datapoints and meaning of the data

e. Lighting system, shading, security system, fire protection system

2. Feedback:

   a. Type, date, location and occupant who submitted the feedback

   b. Comments and votes

3. Occupants:

   a. Name, user profile and preferences

A semantic model comprising all these details of a building, the occupants and their feedback forms a complex, highly interconnected knowledge graph. It is the *digital twin* of the real-world building, formalized with a machine-interpretable language and residing on a computer system.

A challenge consists in populating the semantic model with this detailed data. This is where a BIM can be advantageous, as it can potentially provide all building-related information (point 1), depending on the level of detail of the model.

Fig. 7 shows a model transformation pipeline we implemented, which allows for an automatic processing and extraction of relevant information from a BIM, and its transformation into a semantic model that is compliant with the ontology vocabulary introduced above. The starting point is a BIM of a given building, which is then exported from a BIM tool of choice into the IFC format [13]. The IFC file is then converted with the open-source IFCtoRDF converter [14] to the ifcOWL ontology [15], which is an RDF-based representation of IFC.

Since ifcOWL is an automatic one-to-one translation of the complicated IFC EXPRESS schema into RDF, the resulting structures stay complicated and difficult to navigate and search, which is a serious drawback of IFC. To overcome these issues, and to drastically reduce the model complexity (IFC models contain a highly detailed description of the geometry), our solution performs a further model transformation from ifcOWL into our semantic model via a set of transformation rules encoded as SPARQL (SPARQL Protocol And RDF Query Language) update queries. This results in a leaner semantic model, which is optimized for following causalities (e.g. sequences of `supplies` and `contains` relationships), performing semantic search and applying reasoning. It is noted that the detailed geometry of the building elements is not represented in our semantic model. Instead, the geometric information is processed to obtain more general properties, such as the total floor area or volume of a room.

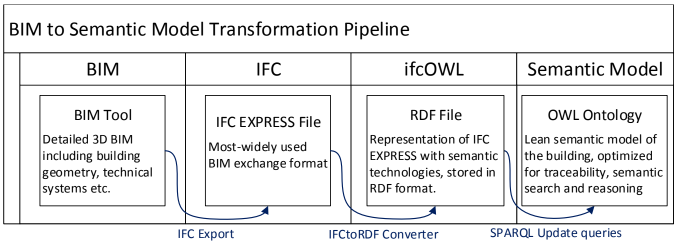

Fig. 7. Transformation of a BIM via IFC and ifcOWL into a semantic model

Whereas building-related information (see 1.) can be extracted from a BIM, all feedback-related information (see 2.) and information about the occupants (see 3.) is collected via the feedback app and is continuously updated in the semantic model with each incoming occupant feedback.

The core classes and properties of the feedback and occupant ontology model are shown in Fig. 8. It uses and extends the PROV ontology (PROV-O) [16] for tracking the provenance of the feedback: *What* feedback was created, *by whom* (object property `prov:wasAttributedTo`), *when* (datatype property `prov:generatedAtTime`), and *where* (object property `prov:atLocation`). The classes and properties stemming from the PROV ontology are the ones starting with the prefix "`prov:`". Besides submitting feedback, occupants can also comment on existing feedback (class `Comment`) or vote for them (object property `votedFor`), which avoids the submission of identical feedback by different occupants and increases their significance.

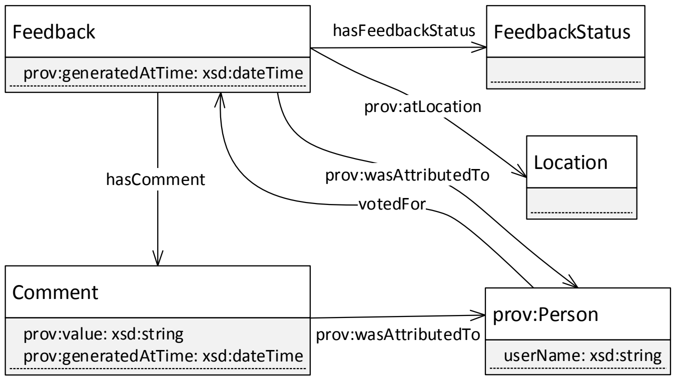

Fig. 8. Ontology model of feedback, occupants (prov:Person), locations and their interrelations. Their provenance is captured with classes and properties from the PROV ontology (prefix "prov: ").

One of the strengths of semantic technologies is the direct applicability of logical rules and reasoning. The identification of possible complaint types for a given location, as explained in Section III, can be implemented by rules that operate on the semantic model. Rules consist of a rule body (IF-part) and a rule head (THEN-part). If the conditions in the body are met, then a rule can be "fired" and the facts defined in the head are derived and added to the semantic model. Fig. 9 shows some example rules for inferring possible complaint types for locations in a building, described in natural language. Such rules can be formalized with SPARQL update queries, SHACL (Shapes Constraint Language) [17] or SWRL (Semantic Web Rule Language) [18]. We chose to use SPARQL update queries in this case, as it allows a direct application on a triple store by a standard SPARQL query engine, without using a reasoner or dedicated SHACL API. The verbally described rules from Fig. 9 needed to be formalized as graph patterns in a way that the rules will match the entities in the semantic model that fulfill the conditions of the rule body. The sometimes complex information structures of IFC required corresponding complex graph patterns inside the rules[1].

Given a semantic model of a building, all the rules are applied to it once, i.e. each rule is executed by the query engine on the knowledge graph. All applicable rules, i.e. the rules whose conditions in the body are met, are fired, and all the possible complaint types per location are derived and explicitly stored in the semantic model. The possible complaint types for a location can then be queried directly from the semantic model via a SPARQL query. Hence, the step "selection of relevant complaint types" (see Section III.A) is finally just an information retrieval on the enriched semantic model.

IF a *room* has at least one *light fixture* in it, **THEN** derive all light-related complaint types as enabled for that *room*

IF a *room* has *air terminals* OR *heaters* OR *chilled ceilings* OR *ventilation systems* OR … in it, **THEN** derive all comfort-related complaint types as enabled for that *room*

IF a *room* is of type *kitchen*, **THEN** derive *TapLeakingComplaint*, *PipeLeakingComplaint* and *SinkBlockComplaint* types as enabled for that *room*

IF a *room* is of type *restroom*, **THEN** derive all restroom-related complaint types as enabled for that *room*

Fig. 9. Rules for inferring the types of complaints that are relevant for the rooms of a building

VI. FIELD TEST RESULTS

The developed solution is being demonstrated in an ongoing field test in a building of Robert Bosch GmbH in Germany, which was retrofitted as a "smart building testbed". The retrofit included wireless radiator thermostats, air flow controllers and temperature and air quality sensors. The testbed is located in a site with several buildings that share the same facility management department. The results presented here are based on the first five months of the field test.

Without including votes, 784 individual feedbacks were submitted in the analyzed period, of which 25 were hardware-related complaints, 645 were comfort-related complaints and 154 were "*commendations*", i.e. the user submitted positive feedback ("I am feeling fine"). The hardware-related complaints were automatically converted into "issue tickets" in the site's facility management system. Comfort-related complaints did not generate any actual tickets, as they were handled automatically by modifying e.g. the blind positions and the temperature, CO_2 concentration and air volume flow setpoints. During the same period, the total of tickets amounted to 4708 in the rest of the site's buildings. The submitted complaints (without including commendations) in the testbed and in the rest of the site can be found in TABLE I.

TABLE I. COMPARISON OF THE NUMBER OF SUBMITTED COMPLAINTS IN THE TESTBED AND IN THE REST OF THE SITE

Building(s)	Hardware-related complaints	Comfort-related complaints	Total
Site (rest)	4705	3	4708
Testbed	25	645	670

The data shows a significant difference in the distribution of complaint types. While in the rest of the site the number of submitted comfort-related complaints is marginal compared to the total amount, in the testbed they are approximately 26 times higher than the hardware-related complaints. On the one hand, this shows that when using the standard complaint submission methods such as online forms and the facility management hotline, comfort-related complaints are seldom submitted, because the effort of doing so is too high. On the other hand, the app was used by occupants to submit complaints that normally would not result in facility management issue tickets, such as complaints regarding the position of the blinds, leading to a strong increase in the number of submissions. Still, comfort complaints that are typically submitted to the facility management, such as those relating to temperature and air quality, represent approximately 40% of the submitted complaints via the app. These results confirm the hypothesis that the developed solution reduces the barrier for occupants to submit complaints. For completeness, it is noted that in the site there are generally no possibilities for the occupants to manually change the temperature or air quality settings; the site's facility management usually manages such changes centrally.

The pie chart in Fig. 10 shows the relative amount of comfort-related feedback types that were submitted. "`Too hot`" complaints as well as complaints related to the blinds were the most popular during the analyzed period.

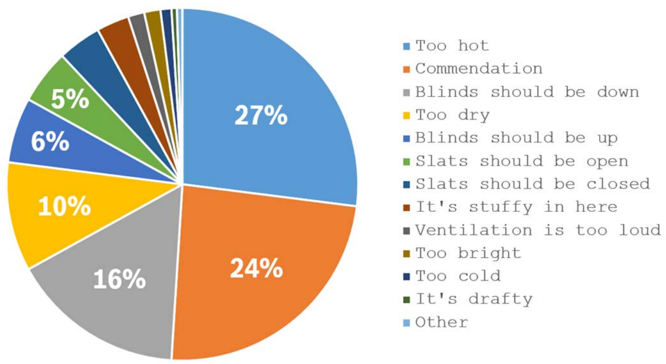

Fig. 10. Relative amount of comfort-related feedback types submitted during the analyzed period

[1] For reasons of space and low readability, we do not show the lengthy SPARQL update queries here

VII. Conclusion

This paper addressed the challenge of designing a software that enables occupants to submit complete and accurate feedback with a low effort. It assumed that classic solutions, such as online forms or telephone hotlines, typically entail a higher effort and thus represent a barrier for the submission of feedback. In the case of comfort issues, not submitting such complaints may lead to the facility management to remain unaware of unsatisfactory comfort conditions or faults, which can result in further issues and costs.

The main solution mechanism we propose is based on the automatic suggestion of complaint types to the user. This is achieved by employing detailed context information stemming from a BIM, the BAS and past complaints submitted by the occupants. This information is integrated and represented with semantic technologies, which allow to formally organize the information and describe the relationships between the data. The solution was implemented as an app and was demonstrated in a real office environment.

The results show that especially the submission of comfort-related complaints increased significantly with the use of the app. While part of this behavior can be explained with complaint types that are typically not submitted to the facility management, around 40% of the additional complaint submissions were due to temperature and air quality issues. Thus, by reducing the effort of submitting complaints with the proposed solution, more accurate information regarding the occupants' actual comfort can be obtained. Moreover, by using the detailed context awareness to also identify the relevant actuators and setpoints, most comfort-related complaints can be handled automatically, thus reducing the facility management's complaint-solving effort.

In summary, the integration of context information offers a high potential to improve the complaint management in buildings. Important enablers are semantic web technologies and BIM, which are becoming increasingly widespread. Especially the growing use of BIM in construction projects [19] could increase the availability of detailed digital information about the building and its technical systems, reducing the barrier to implement solutions such as the one presented in this paper.

Interesting future research topics include the long-term analyses of occupant feedback and the application of machine learning algorithms to improve complaint suggestions.

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