Living Campus: Towards a Context-Aware Energy Efficient Campus Using Weighted Case Based Reasoning

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Abstract

Buildings make a city's landscape and are home to its people. The demand for smart buildings and housing is growing by the need for cities to make their buildings more efficient, green and livable. This emergent intelligence is underpinned by the use of Information and Communications Technology (ICT) linked by Pervasive Sensing and real-time data analytics. In a typical growth of smart buildings, Smart Campuses are going to be amazing community hubs which will be more sustainable, efficient and supportive of its inhabitants. In this regard, huge amount of useful and real-time generated data are being analyzed to help people and machines infer instant decisions in relation to energy efficiency. However, because of different terminologies used by different players, structural, representational and semantic heterogeneity constrain the interoperability between applications and misleads to adaptive and context-aware control behavior. In this paper, the focus is to alleviate the current problem by designing a semantic framework that represents the smart campus data and activities in an ontological model. Also, the framework is deepened by an Artificial Intelligent (AI) method using Weighted Case Based Reasoning (WCBR) for enabling context awareness. An illustration will be the elaboration of an adaptive and autonomous control of HVAC (Heating Ventilation and Air Conditioning) system, in this example the WCBR is discussed and case representation, case adaptation, and similarity computation are sketched in detail.

Introduction

In the USA, given the fact that the country consumes almost 20% of the world's energy, it is very vulnerable to energy scarcity and therefore an effort is made in the direction of energy consumption reduction. In this regards, Living Campus is the centerpiece of the University of Houston which tends to integrate technologies of digital living and provides comfortable, secure, and convenient living style as well as preserving the key elements of energy efficiency. According to similar projects (Guan, Xu, & Jia, 2010), the Living Campus estimates about 30-40% of energy savings by harnessing Information and Communication Technologies. As a matter of fact, energy efficiency lowers the cost of the energy down to 2.8 cents per kWh (Molina, 2014). This perspective put impetus on ICTs communities to enhance the awareness of the cyber, physical, and social contexts and provide essential supports in forms of services, applications, and so forth. Nevertheless, data provided by the pervasive sensor network present multilevel heterogeneity encompassing syntactical, structural and representational dimensions. Thus, it results in a schema conflict and tailor the currently used techniques such as machine learning and interaction models to a specific set of data and sensors. This tight coupling creates a status quo and inhibits the deployment of new technologies into the environment, which in turn significantly reduces the environment's long-term usefulness(Wemlinger & Holder, 2011) (Dendani, Khadir, & Guessoum, 2012).

One solution to that is to consider Context-Aware aspect in Energy Control Operations which allow adapting to the context and catering to highly dynamic environments. Accordingly, Context-Aware Living Campus Ontology (calcont) model was developed in order to provide comprehensive knowledge base that includes different concepts needed to realize energy efficient, intelligent control mechanisms.

In addition, giving the fact that the environment is highly dynamic, the system can't envision all control situations by the ontological-based reasoning. Yet, designing exhaustive list of rules is quiet difficult. In this paper, CBR-based approach is presented as an alternative to Rule Based System. It provides a flexible adaptation control mechanism by its ability to reach inferences and give recommendations based on knowledge from previous problem cases. In addition, the approach denotes a machine learning paradigm that enables sustained and incremental learning with every new experience.

In this paper, a method to support context awareness and handle control operations in the living campus environment is presented. The method is based on knowledge representation and sharing. The outcome is a homogenous, shareable resources environment and a paradigm for supporting context-aware decisions. In addition, an incremental learning paradigm has been sketched with its representation, matching and adaptation steps.

In his section an introduction of this work is presented. In the second section calcont model is presented to facilitate explicit context representation and semantic context sharing. In the third section CBR-based approach for decision making and learning is developed. The fourth section presents the method evaluation and results. Last section concludes this work.

Context Modeling and Reasoning

The ability to take into account the digital and physical environment, and the context of the user makes a space smart. In this work, Context means any information used to describe indoor environment of a space or that can be relevant for its energy efficiency. A space is a bounded place which has some devices and accommodates users' activities.

Semantic Framework of the Living Campus is identified as a paradigm in which various kinds of information from heterogeneous sources are pulled together forming a unified representation model. This representation has to be agreed on and shared by all participating devices and services. This view is enabled by Semantic Web as defined by Berners-Lee as the web of data that creates a universal medium for the exchange of data (Herman, 2001). This vision will enable automated negotiation and retrieval of data and other schemas in Smart Environment (Pasha & Ahmad, 2008). Consequently, the drive to develop Intelligent Distributed Applications has put emphasis on adopting semantic modeling and reasoning of context and W3C standards such as SPARQL for seamless access to data.

Ontology, potentially, provides well-founded mechanism for representing and reasoning over the context and it enables semantic interpretation and information fusion processes. Literally, Ontology is a formally-defined vocabulary for a particular domain of interest, it is generally considered as a set of entities, relations, functions, axioms and instances. The use of ontologies gives several benefits, such as information search and retrieval, knowledge elicitation, knowledge modeling, and knowledge representation. In this vein calcont is designed to represent Campus System capabilities and support interoperation between currently available and future applications of energy efficiency.

In its representation, calcont has stressed three major subsets; **context -** is physical information characterizing the space including indoor climate conditions, weather information and time. **Platform** - inspired from the work on DogOnt ontology (Bonino & Corno, 2008), this concept represents the device that has some roles of sensing or actuating, with its characteristics, functionalities, states and their eventual commands or notification. **User** – describes user profile, preferences and feedback.

Weighted CBR approach for Decision Suppport System

CBR, as proposed by Schank (A. F. Bobick, S. S. Intille, J. W. Davis, F. Baird, C. S. Pinhanez, L. W. Campbell, Y. A. Ivanov, A. Schütte, 1999) , draws on cognitive theories of human memory, problem solving, and Learning (Kolodner & Schank, Roger C. (Ed); Langer, 1994; Leake, 1998). It has been formally described as a cycle with four major steps including representation, Retrieval, Reuse, Revision, and Retention (V. Ricquebourg, D. Durand, D. Menga, B. Marhic, L. Delahoche, C. Loge, 2007). Figure 1 shows the calcont's design.

Case Representations

Case representation is a vital concept in CBR as it allows for better assessment of the similarities of current problems compared to past cases. The knowledge base (case-base) stores information about conditions (problems) and actions (solutions) for previous control situations. Case Ontology is used to represent knowledge of different cases and hold new learning experiences. As a matter of fact, representing cases with ontological model leads to their easy selection owing to the fact that syntactic matching provided by triples form allow for high accuracy and also the search of information using SPARQL language is straightforward and optimized by nature. Case ontology is part of calcont and represents successful experienced controls by description taken decision according to their context. It contains the concept case that describes case types; description, subsumes the case main points (problem and solution); and Index which describes objects involved in the case and integrate the domain model concepts with the rest of the ontology. The figure 1 shows calcont ontology with case ontology part.

Case is primary defined by an auto incremental ID, the other information in the header are EnvironmentID, Control Entity, Timestamp and Survival Value. The context space' features describe the context's attributes in the form (subjects, predicates, objects) as in the triples store. Predicate is a property for the subject of the statement, the subject is the concept involved and object is the range of the predicate. The predicates are biased by weights to express their influence on the control since attributes may not have the same impact over a decision taken. The group of experts establish the ideal weights for the context attributes and the action rate that ideal control strategy should have. Weights are lying in the unit interval and summing to one. In the control space, outcome describes how successful the solution is, the action is the control taken in the case and the feedback is the opinion/reaction of users over this solution. Figure 2 illustrate four different control cases.

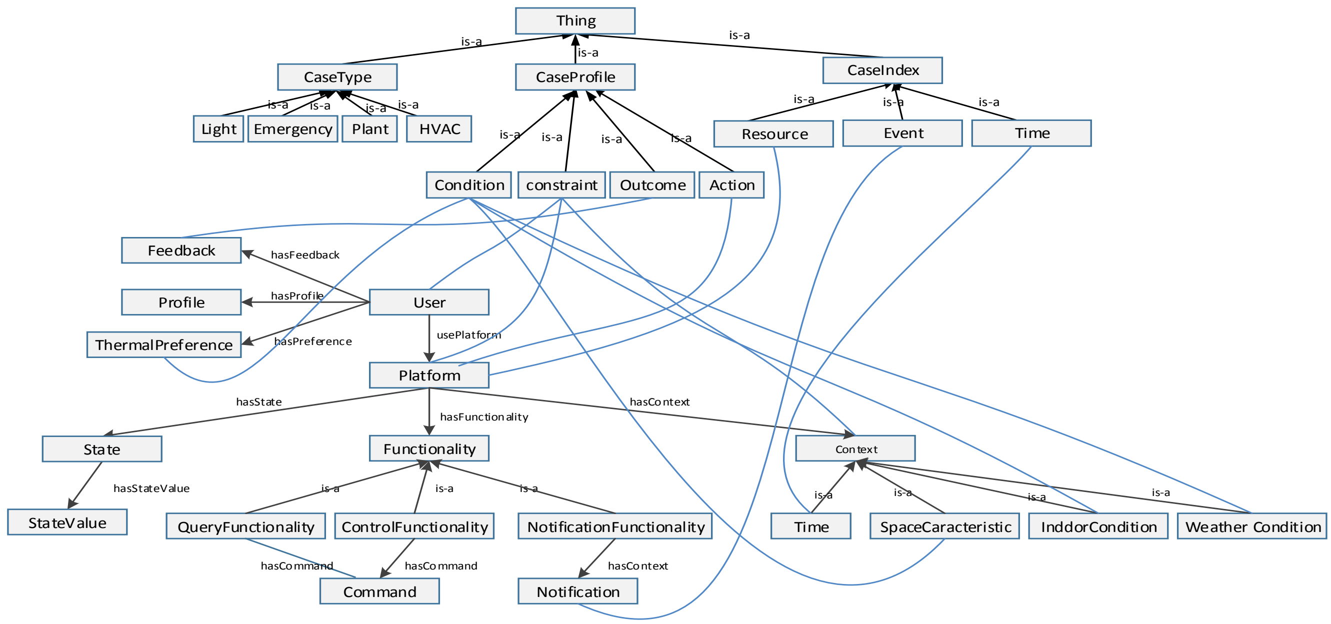

Figure 1 calcont Model representation

Regulate the temperature by occupancy			
CaseID	Control Entity	TimeStamp	Surv. value
C1	HVAC	09/23/14/10:55 am	2.8
Context Space			
Weight	**Subject**	**Predicate**	**Obj**
0.2	Lab221	hasTemperature	73
0.1	HoustonWeather	hasOutsidehumidity	63
0.1	HoustonWeather	hasOutsidetemperature	85
0,2	Lab221	hasCO2	663
0.4	Lab221	hasOccupancy	4
Control Space			
Feedback	Highly Satisfied		
Action	Open Damper **35%**		

Regulate the freshness of the air			
caseID	Control Entity	Date/Time	Surv. value
C2	HVAC	09/23/14 10:55am	1.3
Context Space			
Weight	Subject	Predicate	Object
0.1	HoustonWeather	hasOutsideTemperature	75
0.4	Lab221	hasCO2	950
0.2	Lab221	hasOccupancy	4
0.3	Lab221	hasVolume	679
Control Space			
Feedback	Satisfied		
Action	Open Damper **65%**		

Regulate temperature and humidity when empty of users			
caseID	Control Entity	Date/Time	Surv. value
C3	HVAC	09/20/14/06:55 pm	1.9
Control Space			
Weight	Subject	Predicate	Object
0.1	Lan221	hasType	220
0.1	Lab221	hasTemperature	75
0.1	Lab221	hasHumidity	55
0.7	Lab221	hasOccupancy	0
Solution			
Feedback	Highly satisfied		
Action	Open Damper **51%**		

Regulate the temperature by preference			
caseID	Control Entity	Date/Time	Surv. value
C4	HVAC	09/21/14 09:45am	2.5
Control Space			
Weight	Subject	Predicate	Object
0.3	Lab221	hasTemperature	75
0.7	UserProfile	hasPrefernceVote	68
Solution			
Feedback	Satisfied		
Action	Open Damper **70%**		

Figure 2 Case Representation of four different cases

Matching Cases

Matching serves to measure the degree of similarity between case and context by comparing their triples and features in order to retrieve best cases for a given context. In the matching process, the similarity measure is performed by comparing between case's features and context's data both stored in the RDF triple store and modeled by calcont ontology. The similarity refers to the syntactic similarity because the semantics correlations are already assured by the ontology structure. For this purpose, the String Match (SM) of current context over case-base is calculated. Assuming L is the list of processing concepts in the current context and CC (Case Concepts) is the processing concepts in the case. Processing concepts represents an arrow in the ontology and it's restricted to the subject (domain) and its predicate (property) (e.g. (lab221, hasHumidity)). So, for each case C in the case-base, String Match is calculated by:

$$SM\ (C) = \{x \in L\ /\ \exists y \in CC,\ E(x, y) = 0\}$$

Where E(x,y) is the Evenshtein distance, a similarity functions based on the distance concept. This later returns the string edits operations needed to go from one couple (subject, predicate) into another. It is equal to zero iff strings are equal and it is at most the length of the longer string. The set SM (C) retains the elements of L that are syntactically similar elements comparing to the case C. The SM(C) metric represent the number of concepts in common between the case and the context. To select similar case, a threshold t, defined from experiments, is settled to assess the similarity difference among cases. So, for each case:

$$\begin{cases} \mathrm{card(L)} - \mathrm{card(SM\ (C))} \leq \mathrm{t} & \text{the case is retained} \\ \mathrm{card(L)} - \mathrm{card}\big(\mathrm{SM\ (C)}\big) > \mathrm{t} & \text{the case is declined} \end{cases}$$

Also, As the control can be subject to different context attributes, it's argued that the control case is relevant if the accumulation of common attributes' weights is more than a certain threshold t', given by expert or deduced from experiment. Thus, if the accumulation of common attributes' weights is higher than t', the case is considered suitable for biasing the control decision over the context.

Case Adaptation

It has been argued that adaptation is the most important step of CBR as it adds intelligence to what would otherwise be simple pattern matchers. The adaptation means developing a solution to find a best match set from existing cases. In CBR, the best match sometimes is not a single case, but a combination of cases. For high precision of control, the best match can be the first nearest neighbor of the current context if it exist, elsewhere the best match is a combination of number of solutions which show a similarity tradeoff between the current context and previous cases.

The adaptation allows the calculation of the concluding control rate for the actual context by reusing retrieved past control cases Therefore, to assess attributes' values changes, membership functions are used to apprehend the variances that occur. To draw these functions, the historical records and the range of attributes are used. Therefore, giving a context X, for every retrieved case C, the distance to the context is calculated by Fuzzified Weighted Euclidean Distance using the formula:

$$d(X, C) = (\sum_{i=1}^{i=n} w_i\ (F|x_i - c_i|)^2)^{1/2}$$

Where x_i and c_i are the 'objects' (data properties) corresponding to the triples of matched attributes (subject, predicate) and $F(x_i - c_i)$ is the fuzzified partial distance. For the unique case when there is an identical case (d(X,C)=0), the case's solution is adopted.

Case Retaining

Retaining the case is the process of incorporating the new case into the case-base. This involves the procedure of choosing the information to retain and keep its visibility for future retrieval. For this purpose, each case is associated with a survival value SR which reflects how active the case is in the control system, and serves as a case maintenance basis. The increment or decrement of the survival value of a case depends upon its satisfaction degree. There are different levels of satisfaction, if the case is highly satisfied, that means it's satisfaction degree 'Sat' is more than 0.80; satisfied: $0.65 < Sat < 0.80$; so so: $0.45 < Sat < 0.65$; unsatisfied: $0.25 < Sat < 0.45$ and highly unsatisfied: $Sat < 0.10$.

Initially, when a new case is added in the system, it's given an initial survival degree equal to the threshold to survive. After, when the case is selected for the adaptation of new context, its survival value is updated by:

$$SR^{(new)}(C) = SR^{(old)}(C) + \Delta SR(C)$$

Where $\Delta SR(C) = (Sat(C) - 0.45) \times \alpha$, $\mathrm{Sat}(C)$ is the satisfaction degree (feedback) of users over the case, and α represents the learning rate, set to 0.1 for slowly adjusting $SR(C)$. Otherwise, for new adapted control, its survival value is computed by:

$$\mathrm{SR(X)} = \frac{\sum_{i=1}^{n} Sim(X, C_i) * SR(C_i)}{n} + \Delta SR(X)$$

Where $\mathrm{SR}(C_i)$ is the survival value of the similar case C_i, n is the number of similar cases contributing to the adaptation of X, C_i is i^{th} reference case and $Sim(X, C_i)$ is the solution similarity between X and C_i. And $\Delta SR(X)$ is calculated by the same as selected case. The α is used to balance user satisfaction and case similarity in retaining an adapted case. They can be changed according to how the system prefers user feedback or case similarity.

The system enters the step of Case Retain if the reference solution has a higher user satisfaction (i.e. survival value is over a pre-defined survival threshold $\delta_{survival}$); otherwise the system directly discards the case.

Methods Evaluation and Results

For precise Indoor HVAC control many parameters should be considered such as space characteristics, exterior weather, and number of users, in addition to user profile which handle user preferences and desires. To implement the proposed approach, a prototype has been developed within the confines of the Wireless and Optical Network Laboratory in the college of technology that houses the smart campus mock-up for ongoing researches. The prototype is composed of three sensor nodes per room where each sensor node is composed of a temperature, humidity, occupancy and CO2 sensors that are built on an Arduino board. These sensor nodes communicate with a sensor node gateway that uses Raspberry PI as a hardware component. Every set of Raspberry PI + 3 Arduino nodes represent a wireless sensor network that can be deployed in every room. The gateway of every wireless sensor network sends the data generated by each sensor and communicates it to the open source Middleware on a periodic basis (every 1s). Protégé version 4 is used to represent the ontology and Quest –Ontop- to map the ontology to relational database.

Representation

Earlier in this empirical experience, some controls has been manipulated manually by HVAC experts and feedbacks are collected from users. This experience allow to weight context's attributes, arrange cases' circumstances and store them in the case-base.

Figure 2 shows four selected cases where the context considered was indoor temperature, humidity and CO2 concentration, outside temperature, number of occupancy, room's type, room's volume and capacity. For instance, in the case 1, the decision has been inferred by associating the following parameters: temperature, season, outside temperature, occupancy, with respectively the following weights: 0.4; 0.1; 0.1; 0.4. The following of this experiment is going to be used to prove the CBR-based approach sketched in this paper.

Retrieving

It's worthy to notice that for each control case, the considered parameters don't have equal influence on the decision taken. Having said that, certain contexts have dissimilar parameters from the case already stored, the challenge is to take decision in the existence of unlike context information or in the lack of part of it. Therefore, to retrieve the relevant cases for the context, the case matching algorithm is executed by choosing t=2 which means that cases that have at least 50% of attributes in common with the context query are accepted. The actual context attributes are extracted by querying RDF triples with SPARQL, figure 3 and figure 4 show the request and the result of current context.

From this extraction, the set of processing triples is L= ((Lab221, hasTemperature), (Lab221, hasHumdity), (Lab221, hasCO2)), so for each case C in the case-base, the String Matching is calculated as follow:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
SELECT ?subject ?type ?Object
WHERE {
 ?subject rdf:type ?type
 FILTER ( regex (?subject,"^lab221$") )
 FILTER ( regex (?Time,"ActualTime") )
```

Subject	Predicate	Obj
Lab221	hasTemperature	78
Lab221	hasHumidity	58.5
Lab221	hasCO2	599

Figure 3 actual context extraction

- For C1, SM(L)={(Lab221, hasTemperature), (Lab221, hasCO2)} implies $\mathrm{card(L)} - \mathrm{card(SM\ (C))}$ =2
- For C2, SM(L)={(Lab221, hasTemperature), (Lab221, hasHumidity)} implies $\mathrm{card(L)} - \mathrm{card(SM\ (C))}$ =2
- For C3, SM(L)={ (Lab221, hasCO2)} implies $\mathrm{card(L)} - \mathrm{card(SM\ (C))}$ =1
- For C4, SM(L)={(Lab221, hasTemperature)} implies $\mathrm{card(L)} - \mathrm{card}\big(\mathrm{SM\ (C)}\big) = 1$

So, only case C1 and case C2 are eligible for the matching. Then a second check is performed for common attributes in the non-selected case that have weight accumulation over 0.5 (t' chosen to 0.5). In this test, (Lab221, hasCO2) in case 3 has only 0.3 and the same for (Lab221, hasTemperature) in case 4.

Adaptation

In the adaptation step, the formula of Fuzzified Weighted Euclidean Distance is used to calculate the context distance to the retrieved cases. The membership functions of the three parameters involved in the context is presented in Figure 4.

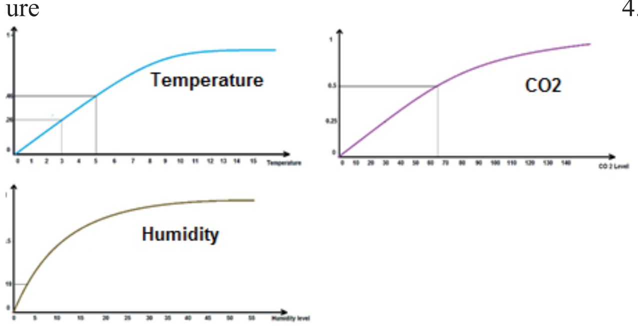

Figure 4 Membership functions of temperature, CO2 and Humidity variances

That is, $d(X, C1)$ and $d(X, C2)$ represent respectively the influence of $C1$and $C2$ respectively on X:

$d(X, C1) = (\sum_{i=1}^{i=n} w_i\, (F(x_i - c_i))^2)^{1/2}$=0.3

$d(X, C2) = (\sum_{i=1}^{i=n} w_i\, (F(x_i - c_i))^2)^{1/2}$=0.29

As shown from distances values, there is no identical case to the context, so the calculation of a tradeoff among the nearest neighbors is directed. AC1 is the action taken in the case C1, which is opening air damper at 35%, and AC2 is the action taken in the case C2 (opening the air damper at 65%). The average of these two values is:

$$\frac{0.29}{0.29+0.3} * 35\% + \frac{0.3}{0.29+0.3} * 65\% = 50.29$$

Which means that the new context has inferred to open the air damper by 50.29%.

After inferring this new control solution, the case-base is updated by new survival values of cases participating in the adaptation process, and the new solution's survival value is calculated based on user's feedback.

Related Work

Smart Cities and Energy Efficiency

Numerous funding agencies such as the National Science Foundation and the U.S. Department of Energy have been funding projects that aim to increase energy efficiency in neighborhoods and cities, adding more renewable energies and reduction of greenhouse gases. Cyber-Enabled Efficient Energy Management of Structures (Braun, R., Hoff, B., Johnson, K., Mehta, D., Moore, K., Simões, M., & Vincent, 2014) sets a goal to integrally and laterally optimize energy consumption within a building using ICT and comprehensive sensing techniques, dynamic graphs and disturbance control for reliability escalation. SEEMPubS (Torino, 2014) aims at increasing green energy by implementing an ICT-based service in public buildings to manage the energy consumption. SEEDS ("Self Learning Energy Efficient builDings and open Spaces," 2014) aims at developing ICT tools for the management of energy use in buildings and open spaces. eDIANA (EU, 2014c) aimed in building's energy efficiency using embedded devices by dividing the control in cells (buildings) and microcell (rooms).

In a wider scale, efforts have been deeply investigated towards supporting cities and regions in taking ambitious and pioneering measures towards lowering energy cost through sustainable use and production of energy. In this vein, IREEN (EU, 2014f) , EFFESUS (EU, 2014d), CONCERTO (EU, 2014b) PLEEC (EU, 2014g) are using a set of strategies and exploiting the best practices in ICTs to realize energy efficiency in the scale of city. CELSIUS (EU, 2014a) demonstrates and promotess the integration of smart district heating and smart district cooling by minimizing its operational costs and carbon emissions while maximizing its energy efficiency. EU-GUGLE (EU, 2014e) aims to demonstrate the feasibility of nearly-zero energy building renovation models in 6 pilot cities in view of triggering large-scale, Europe-wide replication in smart cities and communities by 2020.

Context –awareness

Context-Aware is one of the vital characteristics of smart environment. There are several facets of context-awareness regarding the tackled issue, e.g., interoperability, online reasoning and decision support system, intelligent monitoring and controlling, increased thermal comfort, to cite the most relevant.

In the literature, many works have concerned one or multiple aspects together. In (Ranganathan & Campbell, 2003) the authors propose a context model based on first order predicate calculus to express complex contextual rules which enables automated inductive and deductive reasoning.(Satterfield, Reichherzer, Coffey, & El-Sheikh, 2012) Designed a smart home system with a multi-agent middle layer to study case based reasoning methods for activity recognition by representing and matching among cases using Resource Description Framework RDF-ontology. (García-Herranz, Haya, & Alamán, 2010)proposes an application-independent indirect control programming system to program complex behaviors with the simplicity required to allow unexperienced users to program their smart environments. In this vein, the idea of combining ontology (domain knowledge) with CBR-based systems for knowledge management has been dealt with by many approaches (V. Ricquebourg, D. Durand, D. Menga, B. Marhic, L. Delahoche, C. Loge, 2007) (T. A. Nguyen, A. Raspitzu, 2013) (Stevenson, Knox, Dobson, & Nixon, 2009). But very little or none is explicitly tailored to the needs of energy efficiency and increase of occupant thermal comfort within heterogeneous and dynamic smart environments. This approach shows a process of monitoring and control using context awareness and based on an ontological model that provide the knowledge expansion.

Conclusion

In this work, a context-aware, weighted CBR approach is presented to autonomously control electrical equipment for energy efficiency. The approach is based on an ontological model to avoid interoperability among applications and facilitate the retrieval of information. This Artificial Intelligent method allows to infer contextualized and adaptable controls to support system to take decisions. In addition, unlike existing approaches (e.g. based on complex HVAC control models), this method is a model-free controller and encompasses an incremental learning.

Currently we are evaluating our approach and we are in the process of completing the architecture of our adaptation and learning tool. In the medium term, the objective is to propose a global optimization that involves set of local controls. The challenge is to assure the coherence of the triggering controls while performing global optimization and assessing the global learning from local attainments.

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