Aggregated Performance and Qualitative Modeling Based Smart Thermal Control

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Abstract: In order to ensure thermal energy efficiency and follow government's thermal guidance, more flexible and efficient buildings' thermal controls are required. This paper focuses on proposing an efficient, scalable, reusable, and data weak dependent *smart* thermal control approach based on an aggregated performance and imprecise knowledge of buildings' thermal specificities. Its main principle is to bypass data unavailability and quantitative models identification issues and to ensure an immediate thermal enhancement. For this, we propose, first, an aggregated performance based *smart* thermal control in order to identify relevant thermal setpoints. An extended thermal qualitative model is then introduced to guarantee an efficient achievement of the identified thermal setpoints. Uncertainty about how relevant a thermal control is for a given thermal situation is thus reduced using *online* and preference based learnings.

1 INTRODUCTION

Buildings' energy efficiency has been widely discussed in literature and supported by industrial applications. In fact, buildings are responsible for more than 40% of total energy consumption in Europe (EP&C, 2012) which has led to restricted energy policies for buildings' energy control. As 47% of buildings' energy consumption is used for space heating and cooling (PNNL, 2012), buildings' thermal control has particularly become an important target in order to reduce buildings' energy consumption. Studies on *smart* thermal control are thus relevant and are facing, nowadays, new industrial challenges. The RIDER (Research for IT Driven Energy Efficiency) project is one of recent researches on *smart* thermal control which focuses on the final solution deployment properties. It considers the scalability and reusability of the control solution which lead to a large application area (*i.e.,* form buildings to neighbor-hoods) and deployment costs saving (*i.e.*, neither specific studies, nor particular information, are required for the deployment) of the final solution. Moreover, the RIDER project deals with data availability issues. Indeed, it has to ensure as efficient as possible thermal control whenever sufficient data are available or not. For instance, a new-build that has no historical data can immediately get advantage from the RIDER solution without proceeding by the new-build thermal behavior' study or gathering learning data. This work is part of the RIDER project and proposes a new complete thermal enhancement approach satisfying RIDER's deployment expectations. The proposed thermal enhancement approach provides recommendations starting from thermal setpoints to controls achieving them. This paper explains our overall *smart* thermal control and is organized as follows: first, some *smart* thermal control related works are discussed. Section 3 explains our thermal enhancement approach denoted by RIDER STC (RIDER's *Smart* Thermal Control) which fulfills RIDER's deployment expectations. Conclusions are finally presented.

2 RELATED WORKS

Most buildings' thermal controls are simple and aim to maintain the overall thermal state around a conventional operational point (*i.e.,* indoor tempera-

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ture setpoints). Among well-known thermal regulator, we name TOR (*Tout-Ou-Rien*), P (Proportional action), PI (Proportional Integral action), PID (Proportional Integral Derivative action) control based regulators. P, PI, and PID based regulators implement manual, automatic, adaptive, and identification techniques in order to define the regulator's parameters. For instance, (Zaheer-uddin, 2004) proposes a neural network based approach to update PID control' parameters. Yet, adaptive and individualized thermal control remains not supported by conventional thermal regulators which requires an extra thermal control level (Nassif, 2005); commonly denoted by the *smart* thermal control. As buildings' thermal processes are usually characterized by a slow dynamics and a high inertia, anticipating measurable disturbances related to building's usage, weather conditions, and energy price variations, may lead to a significant thermal control' efficiency enhancement (*i.e.,* decreasing thermal energy consumption, increasing occupants' thermal comfort). Hence, the *smart* thermal control is more than a simple room's temperature control. In order to ensure the *smart* thermal control, additional information on building's usage (*e.g.,* the requested thermal comfort, the building's occupancy profile, *etc.*), climatic conditions (*e.g.,* weather forecasts, sunshine, *etc.*), and energy prices variations, need to be introduced in thermal behavior models which may quickly transform the *smart* thermal control into a complex problem. To solve the complex problem that the *smart* thermal control is, several approaches based either on predictive control techniques or advanced control techniques have been proposed. For instance, we name Homes, OptiControl (Oldewurtel, 2010), and the IC-Berkeley's energy storage (Ma, 2009) projects that propose a predictive control based *smart* thermal control. Applied to the thermal context, the predictive control considers socio-economic objectives such as minimizing energy consumption and maximizing thermal comfort (Ma, 2009). It is based on a mathematical thermal modeling which considers precise quantitative physical aspects of the thermal behavior and explains why mathematical models are also called by *white* type models. In the thermal context, mathematical modeling is supported by software such as TRNSYS, EnergyPlus, SPARK, and SIMBAD which offer a convenient environment for detailed mathematical thermal modeling and thermal simulation. Thus, they can be directly deployed to ensure building's *smart* thermal control. Obviously, the more detailed the thermal mathematical model is, the more efficient the *smart* control would be. However, detailed mathematical design requires expertise, as well as, specific and precise quantitative data and knowledge on buildings' thermal behavior which makes it intricate. Moreover these specific and precise quantitative data are not commonly available for most of buildings which has led to the *grey* type modeling. This last tries to reduce the complexity of mathematical modeling by introducing identification (respectively estimation) techniques in order to complete lacking parameters (respectively input data). For instance, in order to build his monthly energy consumption forecasting model, (White, 1996) has based his thermal modeling on monthly average predicted outdoor temperature rather than detailed forecasts. Identification techniques have been also applied in order to automatically learn thermal parameters such as (Wang, 2006) that has used a genetic algorithm to identify thermal envelop' parameters. Once all thermal parameters/inputs are well identified/estimated, the *grey* type modeling can lead to an efficient and accurate *smart* thermal control. However, building's thermal parameters can only be identified through specific thermal tests also known as building's thermal excitement tests. These tests add an extra deployment constraint to the *smart* thermal control solution. In fact, depending on building's usage, some thermal tests are not conservable which makes building's thermal parameters identification impossible. Although *white* and *grey* models are efficient and accurate for the *smart* thermal control, they do not fulfill RIDER's deployment expectations. In fact, focusing on the accuracy of physical behavior decreases the scalability of *white* and *grey* modeling. Collecting/ operating specific thermal information/tests entails extra costs each time that the *smart* thermal control solution needs to be deployed which means that the thermal enhancement solution is not reusable and cannot be immediately operated unless these information/tests are available/allowed. Based on those observations, Artificial Intelligence (AI) techniques have been introduced 20 years ago in order to ensure the advanced thermal control. They provide a simple, efficient and adaptive *smart* thermal control without requiring any *a priori* know-ledge on thermal physical behavior. AI' learning techniques have been massively applied in order to learn quantitative thermal models also known as *black* type thermal models. (Kalogirous, 2000) have proposed an ANN (Ant Neural Network) based approach in order to learn building's thermal behavior. Therefore, ANN based *smart* thermal control becomes possible and can answer specific questions such as *when is the best moment to restart a heating system after an inoccupation period* (Yang, 2003). Thus, a well-trained ANN thermal model could lead to similar accuracy as *white* and *grey* thermal models. (Aydinalp, 2002) has shown that for cooling' energy cost prediction ANN based modeling is more efficient than the *grey* based one. The supervised leaning technique SVM (Support Vector Machine) has been recently applied in the thermal control area. It has been used for large scale *smart* thermal control (Dong, 2005) and HVAC (Heating Ventilation and Air-Conditioning) systems control (Li, 2009). (Li, 2009) has proven that the SVM based *smart* thermal control is more efficient than the ANN based one. Yet, the main advantage of SVM based *smart* thermal control is that only little information are required for the model training compared to the ANN based one. Training-data are usually collected through *onsite* measurements, surveys, and available documentations. Data pre-treatment and post-treatment are, hence, requested in order to improve the model efficiency (Li, 2009). Therefore, significant computation loads and efficient training-data are required to learn a *black* type quantitative thermal model. However, under real application conditions, thermal data are subject to uncertainty (*e.g.,* whether windows were opened or not), imprecision (*e.g.,* depends on sensors' precision) and incompleteness. Therefore, a *black* model based *smart* thermal control does not totally meet the RIDER's deployment expectations. In fact, the availability of sufficient and efficient training-data is an important factor to determine the *smart* thermal control solution deployment potential. Considering real application conditions, qualitative modeling has been introduced in the thermal control. It is based on the relevance of physical behavior representation which makes it useful to understand complicated physical phenomena. In fact, variables' variation ranges are usually reduced to symbolic sets (*i.e.,* {negative, null, positive}) and qualitative simulations are operated to compute the recommended control option (Kupiers, 1986). In literature, fuzzy thermal rules have been applied for heating systems' control and building's temperature regulation (Dounis, 1995). A review on thermal fuzzy controller can be found in (Singh, 2006). Qualitative model based *smart* thermal control has particularly focused on thermal comfort regulation (Calvio, 2004). Fuzzy predictive control has been also introduced in the *smart* thermal control (Terziyska, 2006). By focusing on the relevance rather than precision, the complexity of the *smart* thermal control is reduced through the qualitative thermal modeling. Indeed, simple thermal control rules expressed by the *Energy Manager* may appear sufficient to ensure a *smart* thermal control which entails no constraint on thermal data availability. Thanks to its data weak dependency property, the qualitative modeling meets all RIDER deployment expectations in order to develop a scalable, reusable, and data weak dependent *smart* thermal control solution. However, ambiguities and lack of accuracy may negatively affect the qualitative modeling efficiency and longevity for a continuous thermal control enhancement purpose.

3 RIDER STC APPROACH

In order to ensure an efficient, scalable, reusable, and data weak dependent *smart* thermal control, we first propose to focus our thermal enhancement approach on thermal setpoints optimization rather than efficiently reaching them. For this, we propose an aggregated performance based reasoning which, unlike the behavioral based reasoning, fulfills RIDER deployment expectations. An aggregated performance allows having an overall assessment on the process. It is built through an aggregation function defined over elementary performances. These last come from the process' output evaluation. An aggregated performance corresponds to the analytic formalization of user's preferences. Occupants' social and preferential lines are then considered once an aggregated performance is used in the thermal enhancement reasoning. Moreover, unlike behavioral models, the deployment of the aggregated performance based enhancement solution does not require any beforehand knowledge on the thermal process which guarantees an immediate improvement of the thermal control. In order to evaluate the expected gain of thermal setpoints' optimization, it becomes unavoidable to deal with thermal behavioral models. For this, we propose an extended qualitative model based *smart* thermal control approach to efficiently reach the optimized setpoints. Well-known qualitative enhancement techniques have been used in our extended thermal qualitative model. These techniques were proposed a long time ago by (Williams, 1989), (Kuipers, 1986) and others, such as (Dubois, 1989), in order to improve qualitative models efficiency and reduce their ambiguities. A survey is proposed in (MQ&D, 1995). For a better understanding, the RIDER STC is explained on one building thermal scale but still easily adaptable for larger thermal scales. For this, the thermal comfort is considered as the aggregated performance used for setpoints optimization. To simplify the optimization problem solving, we introduced a new thermal comfort model denoted by *CIPPD* (Choquet Integral Predicted Percentage Dissatisfied) which is a MAUT (Multi Attribute Utility Theory) version of the *PPD* thermal comfort standard (NF EN ISO 7730, 2006). The reason behind using such formalism is explained in the next section. Then, in order to efficiently reach the optimized thermal setpoints, we introduced a building scale' Extended Qualitative Model (EQM). Time-related information and available quantitative observations have been used in order to improve the EQM reliability and accuracy. Moreover, simplified and generalized thermal behaviors have been considered for the thermal control qualitative modeling which is, also, recognized as a substantial qualitative enhancement technique. Hence, the EQM allows the abstraction of thermal specificities while maintaining a sufficiently relevant representation for thermal enhancement purposes. An EQM based approximate reasoning can thus be generalized for larger and various thermal scales and specificities. Furthermore, the RIDER STC approach does not either requires any particular setting data or important computation loads to be deployed.

In order to ensure a continuous thermal control enhancement, RIDER STC is operated for every new thermal control situation. This last is triggered for every new thermal context and objective. For instance, whenever a thermal context variable (*i.e.,* sunshine, humidity, *etc.*) significantly changes, a new thermal control situation is created in order to adapt the current thermal control. The same goes true when occupants' thermal comfort objectives change (*i.e.,* vacancy periods, personnel change, preference change, *etc.*). The RIDER STC is then an iterative approach which tries to improve continuously the thermal performances. Figure 1 displays an overview of one enhancement iteration of RIDER STC approach. According to thermal context and thermal comfort objectives, the *CIPPD* based control compute new optimized setpoints that are considered by the EQM based control as the new thermal objectives. Depending on the available quantitative data (*i.e.,* historical data), the EQM based control suggests quantitative recommendations to the existing thermal control system (*e.g.,* an HVAC system in Figure 1) which computes thermal equipment's command laws. The operated thermal control is then evaluated by the RIDER STC (*i.e.,* check how much thermal expectations have been satisfied by the thermal control) and saved in RIDER's Database (DB).

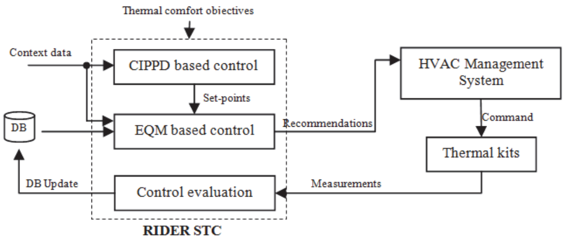

Figure 1: Overview of RIDER STC iterative approach.

Figure 1 highlights, as well, the middleware function of the RIDER STC. In fact, the RIDER STC does not substitute any of the existing thermal regulations but tries to continuously point the correct energy amount (the minimum energy ensuring thermal constraints) from the energy providers to thermal regulators. For this, relevant recommendations on thermal setpoints, heating/ cooling starting time, heating/cooling loads, and so, ensure a personalized and efficient energy usage depending on building/room's thermal specificities.

3.1 CIPPD based Thermal Control

As discussed in section 2, today's *smart* thermal control is only conceived through behavioral thermal process modeling. Considering the thermal comfort performance rather than building's thermal behavior was inspired by bioclimatic architectures. In fact, in such buildings' architecture the economic (energy consumption) and social (comfort) lines are intimately related. The building's location and orientation are considered in the architecture design in order to take advantage of naturally existing climate. For instance, solar radiation and natural air flow are used to, respectively, provide a natural space heating and cooling. Thus, these natural climate elements contribute to maintain occupants' thermal comfort and also reduce thermal energy consumption. Since the thermal comfort is a complex multidimensional concept defined mainly by the indoor temperature but also humidity, radiant temperature, and air flow, we assume that thermal comfort' achievement could be delegated to attributes other than the indoor temperature. Therefore, achieving the expected thermal comfort may be less costly once most of the thermal comfort attributes are considered in the *smart* thermal control. For instance, in winter time, adapting the thermal control *w.r.t.* significant solar radiation fluctuations contributes not only to maintain the requested thermal comfort but also to make the most of solar radiation in order to ensure some free heating needs. Hence, during the day, the indoor temperature setpoint could be adjusted depending on solar radiation prediction which may potentially contribute to reduce buildings' energy consumption. Basing our *smart* thermal control on the thermal comfort performance consists then in identifying, from that last, thermal setpoints satisfying the expected occupants' comfort and leading to as less costly as possible thermal energy consumption. For this, we introduce the *CIPPD* thermal model which matches RIDER's deployment requirements and simplifies its optimization purpose.

3.1.1 CIPPD Model Motivations

Despite thermal comfort inherent subjectivity, standards have attempted to evaluate thermal sensations. The most popular standards are ASHRAE standard 55 and ISO 7730 that, respectively, implement Gagge's and Fanger's thermal comfort models. Gagge's model defines thermal conditions for which at least 80% of individuals would feel comfortable from a thermal point of view (Gagge, 1986). Fanger's model introduces the PMV (Predicted Mean Vote) and PPD (Predicted Percentage Dissatisfied) indexes (Fanger, 1967). The PMV index corresponds to the mean thermal sensation vote expressed on Fanger's scale (*i.e.,* the scale range is defined in [-3,3] which corresponds to human thermal sensation from cold to hot and where the null value refers to the neutral thermal sensation). It is defined through 4 thermal condition variables (*i.e.,* indoor air temperature *Ta*, air humidity *Hy*, air velocity *Va*, and mean radiant air temperature *Tr*) and 2 human parameters (*i.e.,* metabolic rate *Me* and cloth insolation index *Ci*). The PPD index is based on the PMV one and indicates the percentage of thermal dissatisfied persons (1). From a thermal point of view, a person is considered not satisfied when his/her PMV index belongs to $[-3,-2] \cup [2,3]$. Both of the thermal comfort standards are statistical models. They are evaluated in different world parts by asking thousands of people about their thermal sensation in different thermal conditions.

$$PPD = 100 - 95\ e^{\left(-0.03353 * PMV^4 - 0.2179 * PMV^2\right)} \tag{1}$$

Using statistical thermal comfort models for the *smart* thermal control meets RIDER's deployment expectations. In fact, since these models are the result of surveys, they do not require any adaptation to ensure the *smart* thermal control of any building that belongs to the survey's scope. However, the statistical based thermal comfort is usually complex and does not help the optimization purpose that is meant for in our RIDER STC. The complexity of a statistical thermal comfort based control may then significantly increase which entails efficiency problems. Moreover, Gagge's and Fanger's models deal with the thermal comfort concept as a physical phenomenon. Although the body's temperature is related to thermodynamic interactions (*i.e.,* convection, radiation, evaporation, conduction), thermal sensation depends on people preferences and their sociocultural backgrounds. Therefore interaction between thermal comfort' attributes are preferential ones rather than physical which justifies a preference based comfort model. Preference modeling $\succeq$ is a central topic in the Multi Criteria Decision Analysis (MCDA) and measurement theory. Usually, it comes down to find a real-valued overall utility function $u: X \to \mathbb{R}$ that verifies (2) where X corresponds to the alternative set. For multidimensional alternatives, the Krantz's decomposable model (Krantz, 1971) is widely studied. It implements the MAUT theory which consists on assessing any measurement as a satisfaction degree in the [0,1] scale where 0 refers to the worst alternative and 1 to the best one. Measurements are thus made commensurate and interpretable (Fishburn, 1970). Accordingly, the Krantz's preference model is built through utility functions $u_i : X_i \to [0,1]$ defined over each attribute i, where X_i corresponds to the attribute i measurement scale, and an aggregation function F_μ, where μ refers to this latter's parameters (3).

$$\forall x, y \in X \quad x \succeq y \Leftrightarrow u(x) \geq u(y) \tag{2}$$

Krantz's preference model seems quite interesting for the RIDER STC optimization purpose. In fact, it is commonly known that for $\succeq$ verifying both the independence and weak separability properties, F_μ is strictly increasing. Thus, comonotony between u and u_i s holds on X_i. This property is useful to identify simple and interpretable thermal comfort adjustment rules and simplifies the RIDER STC's thermal comfort adjustment. For instance, thermal comfort may be improved when humidity rate increases for one given ambient temperature, whereas it can be disturbed for another one. The coexistence of such rules makes difficult for the *Energy Manager* to decide about attribute variations in order to adjust occupants' thermal control. Hence, Krantz's preference model would greatly simplify the thermal comfort rules design.

$$u(x_1,...,x_n) = F_\mu(u_1(x_1),...,u_n(x_n)) \quad (3)$$

To identify u_i and μ through the one-dimensional measurement scales X_i, the weak difference separability property has to be fulfilled; otherwise the multi-dimensional scale X has to be considered. Hence, the MCDA has introduced interview based approaches in order to identify u_i and μ such as MACBETH which allows identifying them over the decision maker' preferences *w.r.t.* alternatives defined on X. However, proceeding by the interview based approaches to identify the thermal comfort model adds an extra deployment constraint to our RIDER STC solution. In fact, occupants need to be interviewed about their thermal preferences in every building which breaks RIDER's reusability requirement. Therefore, we introduce the $CIPPD$ thermal comfort model where u_i and μ are identified from the PPD index. Basing the u_i and μ identification on a statistical thermal comfort model enables the RIDER STC deployment in any building that belongs to the statistical study scope. The PPD choice is motivated by RIDER's market location which is the EU market. The ISO standard has released an EU PPD version which fits well with RIDER's potential customers. For the PPD identification into Krantz's decomposable model, the Choquet fuzzy integral C_μ aggregation function seems to be the most appropriate model. Namely, fuzzy integrals provide adequate models to capture relative importance of attributes but also preferential interactions among them (Grabisch, 1997). It then allows emphasizing preference relationships among PPD attributes and their relative contribution to the thermal comfort achievement. Since the PPD index is built over a cardinal scale and has a symmetry property regarding the neutral thermal sensation ($PMV = 0$), the PPD representation on a cardinal positive scale seems to be sufficient which again justifies the Choquet Integral. Moreover, the C_μ has linearity property by simplex which goes accordingly with RIDER STC thermal comfort based control.

3.1.2 CIPPD Identification

In order to identify the $CIPPD$ model, (Labreuche, 2011) approach has been adapted to the PPD context. In fact, when F_μ is a Choquet Integral, Labreuche has proposed an original approach to compute both u_i and μ without any commensurateness assumption. Thus, before proceeding by the identification process, MAUT and Labreuche assumptions have to be checked. Let consider N the $CIPPD$ thermal attributes' set built from PPD's thermal condition variables (Ta, Va, Hy, and Tr) and human parameters (Me and Ci). Independency, weak separability and monotony assumption have then to be verified among N's attributes. In next points, we develop and explain these latter assumptions verification in order to approximate the PPD into a Choquet Integral C_μ.

- **Independency Verification**

Structural interactions, such as physical ones, that may jointly influence the comfort overall utility are not tolerated in our $CIPPD$ model. Yet, physical interactions entailed by Me and Ci parameters exist. In fact, Me and Ci do not convey a preferential point *w.r.t.* thermal conditions. They rather illustrate the body energy contribution and clothing insolation in the convective and radiative physical phenomena which make physical interactions with Ta, Va, and Tr attributes obvious. Moreover, for simplification reasons, the radiative phenomena, entailed by Tr, has been considered as convective ones in the PPD model. This simplification leads to physical interaction between Tr and Ta. Therefore, only Ta, Va, and Hy attributes can be considered in the $CIPPD$ preference model. Hence, $N = \{Ta, Va, Hy\}$ corresponds to the $CIPPD$ attributes' set. The $CIPPD$ can thus be identified for given values of Me, Ci and Tr.

Since it is not conceivable to identify a $CIPPD$ model for every possible Me, Ci and Tr values, we restricted our study to administrative buildings where occupants have a sedentary activity rate ($Me = 1,2met$) and similar clothing habits: pant and shirt ($Ci = 0,7clo$). However, radiant temperature Tr is necessary to evaluate thermal comfort and adjust it accordingly to solar radiation variations. The $CIPPD$ model is then defined as (4) where $Me = 1,2met$ and $Ci = 0,7clo$.

To deal with Tr variations, a fuzzy interpolation has been considered. It is defined on five $CIPPD$

models over $Tr \in \mathbf{T}$ where $\mathbf{T} := \{15, 20, 23, 25, 30\}$ and $\mu_{Tr=Tr^*}(Tr)$ refer to the $CIPPD_{Tr=Tr^*}$ membership degrees for $\forall Tr \in [10, 40]$. This decomposition gives the best compromise between the PPD approximation efficiency and the $CIPPD$ complexity.

$$CIPPD_{Tr}(Ta, Va, Hy) = C_{\mu}(u_{Ta}(Ta), u_{Va}(Va), u_{Hy}(Hy)) \quad (4)$$

- **Weak Separability Verification**

For every $CIPPD_{Tr}$, $\forall Tr \in \mathbf{T}$ model, The weak separability property (5) has also to be verified for each attribute $i \in N$ where $(x_i, y_{N\setminus\{i\}})$ refers to a thermal alternative such as x_i corresponds to the attribute i value and $y_{N\setminus\{i\}}$ to attribute' values other than i. To check the weak separability property, for $\forall j \in N \setminus \{i\}$, we have studied the PPD order relationship *w.r.t.* the attribute i values. For instance, Figure 2 shows same iso-temperature shapes which may be interpreted that the Ta order relationship *w.r.t.* Va is invariant. However, the minimum value of PPD is reached for slightly different thermal conditions and, consequently, entails order relationship variation (bordered by the 2 planes). Thus, the PPD does not fulfill the weak separability property on the $X_{Ta} \times X_{Va} \times X_{Hy}$ scale. Yet, the weak separability property can be showed on partitions of the PPD scale.

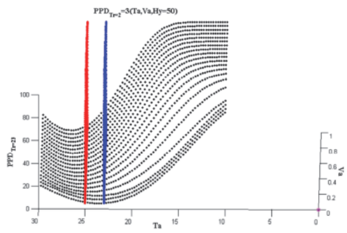

Figure 2: $PPD_{Tr=23}(Ta, Va, Hy = 50)$.

$$\forall x_i, x_i^{'} \in X_i, \forall y_{N\setminus\{i\}}, y_{N\setminus\{i\}}^{'} \in \prod_{j \in N\setminus\{i\}} X_j,$$
$$(x_i, y_{N\setminus\{i\}}) \succeq (x_i^{'}, y_{N\setminus\{i\}}) \Leftrightarrow (x_i, y_{N\setminus\{i\}}^{'}) \succeq (x_i^{'}, y_{N\setminus\{i\}}^{'}) \quad (5)$$

- **Labreuche's Assumption Verification**

In order to avoid saturation problems, Labreuche has supposed strictly increasing u_i functions. In fact, saturation problems are commonly known in interview based u_i identification and consists on similar thermal sensation assessments for slightly different thermal alternatives: $(x_i, y_{N\setminus\{i\}})$ and $(x'_i, y_{N\setminus\{i\}})$, where $x_i, x'_i \in X_i$ and $y_{N\setminus\{i\}} \in \prod_{j \in N\setminus\{i\}} X_j$. Figure 2 shows saturation phenomenon *w.r.t.* Va variations. Moreover, iso-temperature functions (Figure 2) show a PPD gradient sign variation *w.r.t.* Ta. This observation can also be intuitively noticed. In fact, in winter time, it is obvious that an increasing Ta is appreciated until an upper threshold, above it people get hot and their thermal sensation progressively decreases which implies at least one monotony variation of the u_{Ta} function. In the next section, we explain how the weak separability and monotony property have been verified to identify $CIPPD_{Tr}$.

3.1.3 CIPPD Thermal Comfort Model

Since the PPD does not fulfill the weak separability and monotony properties on the $X_{Ta} \times X_{Va} \times X_{Hy}$ scale, one Choquet Integral cannot be identified for each $CIPPD_{Tr}$ model, $\forall Tr \in \mathbf{T}$. Yet, the continuous and regular PPD variation *w.r.t.* its attributes let think that $CIPPD_{Tr}$ can be identified on PPD's scale partition $X_{Ta}^{'} \times X_{Va}^{'} \times X_{Hy}^{'}$ that satisfies MAUT and Labreuche assumptions. According to Figure 2, 2 partitions seems sufficient to cover most of the PPD scale for each $CIPPD_{Tr}$, $\forall Tr \in \mathbf{T}$. Therefore, the Labreuche approach has been applied in order to compute u_i and μ for each $CIPPD_{Tr}$ partition without any commensurateness assumption.

The $CIPPD_{Tr}$ models' partitions have been defined using Labreuche commensurateness verification approach. In fact, to check N's attributes commensurateness and automatically compute attributes' commensurate values: $\mathbf{1}_i$ and $\mathbf{0}_i$ (*i.e.,* $u_i(\mathbf{1}_i) = u_j(\mathbf{1}_j)$ and $u_i(\mathbf{0}_i) = u_j(\mathbf{0}_j)$, $\forall i, j \in N$ and $i \neq j$) which refer, respectively, to good and unacceptable satisfaction degrees *w.r.t.* the attribute i, Labreuche has proposed to study the gradient function related to x_i *w.r.t.* $x_{j \in N\setminus\{i\}}$ variations. It comes on studying function (6)'s shape: a constant function means that no interaction exists between attributes i and j; otherwise, preferential interactions exist between attributes i and j, and the commensurate value x_j^*, where $u_i(x_i) = u_j(x_j^*)$, can, thus be computed. For this, at least one attribute reference values $\mathbf{1}_i$ and $\mathbf{0}_i$ need to be given in order to compute other attributes commensurate values. For more information please refer to (Labreuche, 2011) (Denguir, 2012).

$$i, j \in N, i \neq j, \varepsilon > 0$$
$$f_i : x_j \mapsto PPD(x_i + \varepsilon, x_{N\setminus\{i\}}) - PPD(x_i, x_{N\setminus\{i\}}) \quad (6)$$

For the $CIPPD_{Tr}$ construction, $\mathbf{1}_{Ta}$ and $\mathbf{0}_{Ta}$ references have been considered. They come from the PPD iso-temperature functions study where $\mathbf{1}_{Ta}$ have been chosen according to PPD's minimum value which, consequently, entails the best occupants' thermal satisfaction. Therefore, basing on (6), $\mathbf{1}_{Va}$, $\mathbf{0}_{Va}$, $\mathbf{1}_{Hy}$ and $\mathbf{0}_{Hy}$ commensurate values have been atomically computed and the $CIPPD_{Tr}$ partition scales identified. Utility functions u_i^{Tr} and Choquet Integral parameters μ_i^{Tr} can, then, be identified for every partition $X_i^{'} \subseteq X_i$, where $Tr \in \mathbf{T}$, $i \in N$. For numerical details please refer to (Labreuche, 2011).

3.1.4 Thermal Comfort Adjustment Rules

Our thermal comfort model relevance can immediately be proven through its ability to auto-generate thermal comfort adjustment rules. In fact, thanks to the co-monotony between $CIPPD_{Tr}$ and u_i^{Tr} functions, $\forall i \in N$, interpretable thermal adjustment rules can easily be identified as (7) where ∇u_i^{Tr} and $\nabla CIPPD_{Tr}$ refer to the approximate gradient of u_i^{Tr} and $CIPPD_{Tr}$.

$$i \in N, X \in X^{'},\ \mathrm{sng}(\nabla u_i^{Tr}) \rightarrow \mathrm{sng}(\nabla CIPPD_{Tr}) \tag{7}$$

Moreover, in each $CIPPD_{Tr}$ partition the influence of each thermal attribute (*i.e.,* δTa, δVa, and δHy) on the $CIPPD_{Tr}$ can easily be estimated (8), where $\Delta\mu_i^{Tr}$ refers to the Choquet Integral approximate parameter. This result is all the more useful than the Choquet integral is linear by simplex (Denguir, 2012). Obviously, the efficiency of the estimated gain can be discussed since it corresponds to the fuzzy interpolation result; however, it remains helpful for recommendation purposes. These thermal comfort rules can immediately be applied by the *Energy Manager* since they are interpretable as satisfaction degrees which is different from the PPD where thermal attributes' influences on the PPD are neither obvious to identify nor interpretable for the *Energy Manager*.

$$\delta CIPPD_{Me=1.2, Ci=0.7, Tr} = \Delta\mu_i^{Tr}.\nabla u_i^{Tr}.\delta i \tag{8}$$

3.1.5 CIPPD based Energy Consumption Optimization

The $CIPPD$ based *smart* thermal control consists on adjusting thermal setpoints in order to reduce thermal energy consumption while maintaining the requested thermal comfort. For this, room specificities (*i.e.,* occupant thermal comfort requirement, solar radiation exposure) can be considered to ensure a room customized thermal control. For instance (9) corresponds to thermal setpoints variation identification in order to ensure as less as possible energy consuming thermal comfort c_k^*, where k belongs to the building room' set R. (9) assumes that the indoor temperature control is the most energy consuming. Therefore, minimizing δTa entails energy saving. It has to be noted that thermal setpoint adjustment depends on the equipment availability. For instance, δHy adjustment is only relevant when humidity control kits are available in the building.

$$\begin{cases} \min \delta Ta_k \\ s.c. \\ CIPPD_{Tr}(Ta_k + \delta Ta_k, Va_k + \delta Va_k, Hy_k + \delta Hy_k) \geq c_k^* \\ \forall k' \in R \setminus \{k\}\ CIPPD_{Tr}(Ta_{k'}, Va_{k'}, Hy_{k'}) \geq c_{k'}^* \end{cases} \tag{9}$$

The optimization problem (10), where $\alpha_{kk'}$ is an approximate thermal exchange rate between rooms k and k', considers the solar radiation exposure and variation during the day $Tr(t)$ in order to adjust thermal setpoints depending on radiant temperature. Therefore, for every significant δTr_k, thermal set-points are adjusted. Thus, the requested thermal comfort is maintained and natural elements such as the solar radiation is used in order to ensure parts of heating necessities and then reduce the thermal energy consumption.

$$\begin{cases} \min \sum_{k \in R} \alpha_k \,|\, \delta Ta_k \,|,\ \alpha_k = \sum_{k' \in R} \alpha_{kk'} \\ s.c.\ \forall k \in R, \\ CIPPD_{Tr_k(t)}(Ta_k + \delta Ta_k, Va_k + \delta Va_k, Hy_k + \delta Hy_k) \geq c_k^* \end{cases} \tag{10}$$

The $CIPPD$ based *smart* thermal control can, also, be used to adjust thermal setpoints according to the context variation such as: raining days and building' occupancy variation. Note that these optimization problems are simplified thanks to the Choquet linearity by simplex property.

3.2 EQM based Thermal Control

The EQM based *smart* thermal control tries to reproduce an approximate reasoning in order to efficiently achieve the optimized thermal setpoints computed in Section 3.1. In fact, when we are not familiar with buildings' thermal behavior, thermal control of buildings may seem intricate. Uncertainty about how relevant a thermal control is for a given thermal situation, is then in its highest level. The same reasoning remains true for the control of any complex system. However, objective observations (*i.e.*, vaguely identified physical behavior) and subjective ones (*i.e.*, human preferences) may contribute to reduce uncertainty about thermal control. Therefore, we introduce our EQM which is used to represent simplified thermal control rules. It, also, defines how these thermal control rules should be applied to ensure the control enhancement for different thermal situations. The EQM design is based on influence approximations relating thermal control parameters to thermal performances. In order to extend thermal qualitative modeling, the EQM's parameters and performances display time-related information about thermal general behavior. The influences, among parameters and performances, are vaguely identified from thermal general behavior and their accuracy is constantly improving through *online* thermal quantitative observations. Therefore, keeping track of predate thermal control, as well as, their performances allow recalling them in similar control situations. A Thermal Control Manager (TCM) has then been conceived in order to maintain thermal historical data. For each thermal control attempt, the thermal situation, controls and performances are, then, stored by the TCM. This last is described by the following set $TCM = \{k=1..n, (S^k, CMD^k, PERF^k)\}$ where n is the number of previous thermal experiences and S^k, CMD^k and $PERF^k$ are, respectively, the k^{th} thermal situation (*i.e.,* outdoor and indoor temperatures, *etc*.), controls and performances. To support comparison over the previous attempts and apply approximate reasoning, AI techniques have been deployed. Figure 3 displays the EQM based *smart* thermal control general approach; S^{new} refers to a new thermal situation for which an efficient thermal control needs to be computed. It, mainly, involves indoor and outdoor thermal current situations, as well as, thermal setpoints, computed by the $CIPPD$, that need to be reached before occupants show up.

Since the EQM uses quantitative thermal experiences to improve its accuracy, TCM's quantitative knowledge need to be filtered before proceeding by the EQM accuracy enhancement. Therefore, step 1 of Figure 3 allows quantitative linear reasoning around S^{new}. The most favored thermal experience $(S^*, CMD^*, PERF^*)$ (*w.r.t.* the current situation) for the linear quantitative reasoning is computed by step 2. The EQM thermal enhancement rules are applied in step 3 in order to compute a more likely *better* command law CMD^{new} from CMD^*. In fact, since the EQM influences have been approximated using thermal objective and subjective knowledge, thermal enhancement control can be operated. Contradictory influences on thermal performances can, simply, be resolved by considering user's priorities. For instance, building's occupants may be more demanding about their thermal comfort. The EQM will, thus, give priority to optimize thermal comfort related performances. Hence, thanks to the EQM influences, it becomes possible to recommend control parameters increase/decrease. CMD^{new} is finally applied and evaluated in Figure 4's step 4. In this paper, we particularly focus on particular features used to extend the qualitative thermal modeling. For this, we explain the time-related, simple behavior analysis, and quantitative observation used in order to extend our EQM's qualitative modeling.

EQM STC (S^{new} , TCM)
  if $TCM = \varnothing$ then call the energy manager else
    1. Compute $TCM^* \subseteq TCM$ where, $\forall (S, CMD, PERF) \in TCM^*$, S is similar to S^{new}
    if $TCM^* = \varnothing$ then call the energy manager else
      2. Find $(S^*, CMD^*, PERF^*) \mid \forall (S, CMD, PERF) \in TCM^*$, CMD^* is most favored for S^{new}
      3. Compute CMD^{new} for S^{new} based on the EQM and the quantitative information of CMD^*
      4. Apply CMD^{new} and update the TCM with the new attempt $\left(S^{new}, CMD^{new}, PERF^{new}\right)$
    end if
  end if
end

Figure 3: EQM based *smart* thermal control approach.

3.2.1 Time-Related Information

In order to ensure RIDER deployment expectations, our EQM applies an event-based representation (Montmain, 1991) for thermal control laws. This latter is more relevant than a classical sampled time representation in a qualitative approach. It is, also, considered sufficient for the thermal control laws' description since steps and ramps signals are usually used for the thermal regulations. In order to involve time-related information, the EQM considers thermal control starting time which is useful to improve control delays. Therefore, for each thermal control law $\mathcal{L}(t)$ we associate a control parameter vector $C = (\Delta t, \Delta p, \Delta y)$. *CMD* refers to the set of control parameters vectors C applied on all building's actuators. These 3 control events are described by the thermal example showed in Figure 4 and refer, respectively, to $\mathcal{L}(t)$ delay (time-gap between $\mathcal{L}(t)$ starting time t_1 and thermal control starting time t_0), gradient (characterized by the time-gap between $\mathcal{L}(t)$ highest y_1 and lowest y_0 values) and amplitude (height-gap between $\mathcal{L}(t)$ highest and lowest values). Moreover, time-related information are considered in the EQM' performances modeling. In fact, rather than building's thermal profiles, thermal performances are considered to ensure RIDER deployment expectations. Indeed, the performance vector $P = (cost, comfort, flexibility)$ describing thermal energy consumption, stationary thermal comfort and setpoints' achievement delay, ensures building's thermal assessment. *flexibility* shows time-related information which makes time-related control enhancement possible. *PERF* corresponds then to the set of all building's rooms thermal performance vectors P.

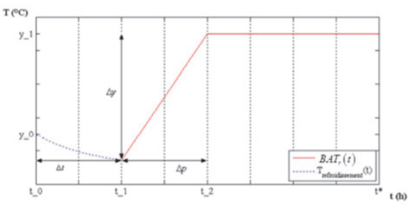

Figure 4: EQM's control events.

3.2.2 Simple Thermal Behavior Analysis

General and simple thermal behaviors have been studied in order to identify how each control parameter influences the considered thermal performance. For instance, (11) describes one room temperature profile $T(t)$ when applying the command law $\mathcal{L}(t)$, where Te, λ and α refer, respectively, to the outdoor temperature, room passive resistance coefficient and thermal loss coefficient. Hence, identifying the λ and α coefficient does not concern the EQM modeling since it implies buildings' excitement scenarios constraints, however, (11) is useful to study thermal performance monotonies *w.r.t.* command parameters variations. The result of this study can, thus, be immediately applied on any building without requiring any extra information on building's thermal process.

$$\frac{dT(t)}{dt} - \lambda(\mathcal{L}(t) - T(t)) - \alpha(Te - T(t)) = 0 \qquad (11)$$

Table 1 describes gradient directions computed over each performance *w.r.t.* each control parameter. Considering gradient directions rather than precise derivative values ensures the RIDER deployment expectations. For each performance j, where $j \in S_P$ and S_P is the considered thermal performance set (*e.g.*, $S_P = \{cost, comfort, flexibility\}$), and control parameter i, where $i \in S_C$ and S_C is the considered control parameter set (*e.g.*, $S_C = \{\Delta t, \Delta p, \Delta y\}$), an influence function F_{ij} : $V_i^C \times V_j^P \rightarrow \{-, 0, +\}$ is defined, where values of thermal control parameters c_i, $\forall c_i \in S_C$, and performances p_j, $\forall p_j \in S_P$, are, respectively, defined in V_i^C and V_j^P. F_{ij} indicates whether the performance j increases (+) or decreases (-) *w.r.t.* i variations. A (0) valued F_{ij} function indicates that i has no influence on j. The F_{ij} qualitative gain can, thus, be represented by the EQM and results from studying gradient directions of simplified thermal behaviors such as (11). For instance, it is commonly known that, in winter time, thermal energy consumption ($cost$) increases by increasing the command law height (Δy). This is illustrated, in Table 1, by a constant influence function describing a gradual rule type on $V_{\Delta y}^C \times V_{cost}^P$ such as the greater the heating step amplitude is, the greater the thermal energy consumption would be. Therefore, regardless of buildings thermal specificities, F_{ij} can be deduced from simplified physical behaviors (*e.g.*, $F_{\Delta y\, cost}$).

Table 1: EQM influence modeling (0 means no influence).

S_C / S_P	Δt	Δp	Δy
cost	$F_{\Delta t\, cost}(c_{\Delta t}, p_{cost})$	–	+
comfort	0	0	$F_{\Delta y\, comfort}(c_{\Delta y}, p_{comfort})$
flexibility	–	–	+

Buildings' special features can occasionally be responsible of F_{ij}'s sign variations (*e.g.*, $F_{\Delta t\, cost}$). In this case, influence functions are subject to uncertainty problems that are handled by considering quantitative observations in the EQM based reasoning.

3.2.3 Quantitative Observations

Uncertainty about some influence function may negatively affect the EQM efficiency. However considering thermal quantitative observations, uncertainty about gradient directions is reduced according to new thermal observations. Moreover, the qualitative based reasoning may seems lacking for continuous enhancement purposes. Nevertheless, combining the qualitative reasoning to quantitative observations makes the control enhancement more accurate and seems to be sufficient for the EQM based *smart* thermal control. In this section, we explain how quantitative knowledge has been considered to reduce uncertainty about influence functions and how the EQM reasoning has been made more accurate using the TCM quantitative thermal experiences.

- **Decreasing EQM's Uncertainty**

In order to reduce uncertainty about the EQM influence functions, objective and subjective knowledge has been considered. Objective knowledge corresponds mainly to interpretable physical phenomena. When uncertainty about F_{ij} functions holds, simple learning techniques are applied over TCM's previous thermal experiences in order to specifically identify each building's bending points. For instance, $F_{\Delta t\ cost}$ depends on building ventilation and insulation properties: starting the heating process earlier or later impacts differently the thermal energy consumption. Figure 6 shows some possible shapes of the continuous function relating $c_{\Delta t}$ to p_{cost} values. The shape of this function is obtained from the simplified thermal behavior model (*i.e.,* in some cases, the continuous function relating $c_{\Delta t}$ to p_{cost} displays a maximum. Otherwise it is decreasing for any $c_{\Delta t}$ value). The maximum remains to be identified. Figure 5's displayed maximums can be explained by the fact that, when outdoor temperature is lower than the indoor one, building's ambient temperature decreases until the control law is started. The $c_{\Delta t}$'s interval for which p_{cost} increases refers to situations where it is more costly to start heating for a short time from a low temperature than heating the building for a longer time but starting from a higher temperature. The decreasing p_{cost} *w.r.t.* $c_{\Delta t}$ refers to the opposite behavior. Furthermore, the HVAC system is responsible for the rapid decrease of building's ambient temperature when the heating system is off. In fact, the HVAC continuously injects a weak percentage of the outdoor air for ventilation purposes. Therefore, we propose to use TCM's quantitative knowledge to capture, for each building, the $c_{\Delta t} \in V_{\Delta t}^{C}$ value that entails sign variation in the continuous function (Figure 5) and finally *online* learn $F_{\Delta t\ cost}$ influence function. We have introduced a possibility based approach in order to continually reduce uncertainty about EQM's influence functions. More complicated buildings' thermal dependent influence functions have been thus considered. For more information, please refer to (Denguir, 2014).

Subjective knowledge can also be used in order to reduce uncertainty about buildings thermal control. For instance, the *CIPPD* thermal comfort model can contribute to identify the $F_{\Delta y\ comfort}$ function (Table 1). Therefore, building's occupants thermal sensations and thermal context variations (*i.e.,* humidity and sunshine) are considered while identifying $F_{\Delta y\ comfort}$. In fact, depending on the thermal context, an increasing Ta may either improve or distract the occupant's thermal comfort. Hence, $F_{\Delta y\ comfort}$ acknowledge sign variations since thermal command law height influences Ta. The *CIPPD* formalism helps $F_{\Delta y\ comfort}$ identification since $\text{sng}(\nabla u_{Ta}^{Tr})$ provides its values.

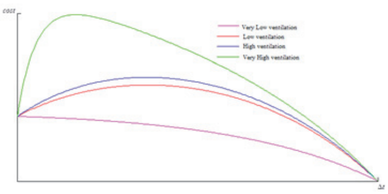

Figure 5: p_{cost} w.r.t. $c_{\Delta t}$ variations from different ventilation perspectives.

- **Improving EQM's Accuracy**

Step 3 of Figure 3 shows that the EQM based *smart* thermal control is built from the EQM qualitative reasoning on the quantitative thermal command CMD^* which makes it more accurate. For instant, (12) shows how one actuator Δt parameter ($C_{\Delta t}^{new}$) can be precisely evaluated considering predate quantitative experience and particularly the $C_{\Delta t}^{*}$ command parameter and $P_{flexibility}^{*}$ performance. Therefore, deciding about the most likely favored TCM predate thermal experience, to be used in the EQM reasoning, is an important issue and corresponds to Figure 3's step 2.

$$C^{new}_{\Delta t} = C^{*}_{\Delta t} - P^{*}_{flexibility} \tag{12}$$

Our EQM quantitative enrichment is decided among the TCM prior experiences considering 3 decision criteria:

i. Similarity between previous situations S and the new one S^{new}: it allows overcoming non-linearity problems related to thermal controls (step 1 of Figure 3) since maximizing the similarity allows linear quantitative reasoning around a setting point. Similarity between thermal situations is based on a distance $dist(S', S'')$, where S' and S'' are two thermal situations. The smaller $dist(S', S'')$ is, the more similar S' and S'' would be. Since thermal situations are only defined by temperature measurements, there are no commensurateness problems in $dist(S', S'')$ definition.

ii. Thermal performances: Obviously, the better the resulting thermal performances $PERF$ are, the more favored the control experience would be. For this, MCDA techniques have been deployed. A preference model over the considered performances S_P is identified. Firstly, utility functions (u_{cost}, $u_{comfort}$ and $u_{flexibility}$) are defined for each performance to ensure commensurability. They allow the assessment of each performance over the same scale which is the satisfaction degree or utility scale [0,1]. Secondly, an aggregation function is required in order to ensure the overall thermal evaluation $\mathcal{P}_r^k$ for each room $r \in R$ (R corresponds to the building rooms' set) and prior thermal control experience k. These steps are related to the *Energy Manager* preferences which depend on his *Energy Policy*. Interview based approach such as MACBETH can be applied in this case. We assume that a weighted sum is sufficient to capture this preference model. When thermal control is related to a subset of rooms $R' \subseteq R$, overall thermal assessment has to consider all thermal performances over R'. Thus, our EQM proposes to proceed firstly by aggregating all performances over R' from the energy consumption (sum), thermal comfort (min) and flexibility (max) points of view; secondly, the preference model defined for one room is applied for R'. We denote by $\mathcal{P}^k$ the overall building thermal assessment associated to the k^{th} ($PERF^k$) prior thermal experience stored by the TCM.

iii. Previous enhancement results: predate controls that have led to thermal enhancement failures are penalized in future TCM evaluations. Therefore, we associate a set Bad^k to each $(S^k, CMD^k, PERF^k) \in TCM$. Bad^k gathers prior thermal experiences that were computed from $(S^k, CMD^k, PERF^k)$ and led to thermal performance decreases.

Considering these 3 criteria, an overall score $score^k$ (13) can be computed for each TCM experience in a limited neighborhood of S^{new} (to satisfy the thermal process linear quantitative behavior expected property). The quantitative information $(S^*, CMD^*, PERF^*) \in TCM$ favored for our EQM enrichment verifies: $score^* \geq score^k$ $\forall (S^k, CMD^k, PERF^k) \in TCM$. Quantitative knowledge can then be used to make more accurate the EQM reasoning.

$$k \in \{1,..,n\},\ score^k = \{1 - dist(S^k, S^{new})\}.\mathcal{P}^k * \prod_{k' \in Bad^k} \{1 - dist(S^{k'}, S^{new})\}\mathcal{P}^{k'} \tag{13}$$

4 CONCLUSIONS

In order to fulfil RIDER deployment expectations, we have proposed the RIDER STC solution which considers the CIPPD and EQM based reasoning in one building scale. The CIPPD based reasoning allows the identification of the most relevant thermal setpoints in order to improve the thermal comfort and reduce thermal energy consumption. Once the optimized setpoints are provided, the EQM based reasoning says how they can be efficiently achieved. It implements an iterative approach that provides thermal control recommendations as soon as it is deployed without needing any *a priori* learning or identification. These control recommendations are then refined thanks to quantitative observations and qualitative physical aspects related to thermal processes. When using the CIPPD based control, our experimentations let expect about 10% of thermal energy consumption decease. Combined to the EQM based *smart* thermal control, RIDER STC solution reveals, for one room, about 7 to 31% of thermal energy consumption decrease and 12 to 24% for multi-room thermal enhancement. Average thermal energy consumption decrease ensured by the RIDER STC is evaluated to 16% which is significant considering energy prices. How the RIDER STC can bypass frequent thermal control deployment issues such as quantitative data availability, can be considered as an outstanding point compared to the existent thermal control solutions. Just the CIPPD based *smart* thermal control can be considered as a remarkable shift in how *smart* thermal control has been considered till these days. Comparing the EQM based *smart* thermal control efficiency with commonly used approaches (based on *white*, *grey* or *black* thermal models), is unbalanced considering their different application conditions. In fact, trying to operate an MPC (Model Predictive Control) in few days on a completely unknown building is not conceivable. It goes the same when asking the EQM based control for the same efficiency as a MPC based control in a fully identified building's thermal process. Yet, perspectives remain possible to improve RIDER STC efficiency. For the CIPPD based *smart* thermal control, adaptive and dynamic thermal comfort model could be considered in order to ensure more personalized and individualized thermal comfort adjustment. Yet, the PPD's choice satisfies the data unavailability issues. The transition toward an adaptive and dynamic thermal comfort model shall, thus, be supported by *online* learning techniques. The CIPPD identification could also be improved by using bipolar utility scale wish gives more expressivity to the thermal comfort models and could lead to a better approximation of the PPD function. The EQM based *smart* thermal control provides a methodology in order to improve the qualitative based thermal control efficiency. Therefore, each step implementation technique could be discussed. For instance, uncertainty management in influence functions can be improved. Ambiguous measurements coming from thermal disturbances (*i.e.,* windows and door opening) should complete this point. Sensors data precision can be studied as well. Qualitative interactions between the control enhancement parameters could also be studied in order to compute enhancement recommendations based on subsets of control parameters variations instead of singletons. This will warrantee the EQM control convergence to a global improved control experience rather than a local one. The scalability of the RIDET STC solution could also be discussed. In fact, we have shown in section 3.2.3 that multi-room transition needs some settings and it goes the same for any scale transition. The scalability could have been made automatic by providing different scales templates in the RIDER STC final solution. This task is simplified thanks to the EQM modularity.

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