Approximate Reasoning for an Efficient, Scalable and Simple Thermal Control Enhancement

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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 scalable, efficient and simple thermal control approach based on imprecise knowledge of buildings' specificities. Its main principle is a weak data-dependency which ensures the scalability and simplicity of our thermal enhancement approach. For this, an extended thermal qualitative model is proposed. It is based on a qualitative description of influences that actions' parameters may have on buildings' thermal performances. Our thermal qualitative model is enriched by collecting and assessing previous thermal control performances. Thus, an approximate reasoning for a *smart* thermal control becomes effective based on our extended thermal qualitative model.

Keywords: Qualitative modeling, approximate reasoning, *smart* thermal control, *online* learning, preference based learning.

1 Introduction

Since the first oil crisis in 1974, buildings thermal regulation, in France, has become stricter and harder to fulfill. Thus, highly developed thermal control techniques became mandatory in order to fulfill the government's thermal guidance and decrease buildings energy consumption. However, in spite of the big advances in thermal technologies (*e.g.,* thermostat), *smart* thermal control suffers from deployment issues (*i.e.*, deployment costs, significant settings, significant measurement, *etc.*). In fact, the uniqueness of each building complicates the design of sufficiently efficient and widely applicable thermal controls which leads to additional costs each time that the solution needs to be deployed in a different building. Therefore, *smart* thermal control related researches remain relevant and focus mainly on efficient and highly reusable aspects of thermal control approaches. This paper's work can be referenced in this latter research area and contributes to building's thermal performance enhancement. *Zero Learning Data* and *Zero Setting Parameters* challenges are, hence, considered in this paper studies. For this, we propose a new approach (THPE: THermal Process Enhancement) based on an Extended Qualitative Model (EQM) in order to bypass the

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complexity of quantitative modeling and the insufficiency of qualitative ones. In fact, the EQM is based on a relevant, rather than precise, thermal enhancement modeling and an approximate, rather than accurate, reasoning. These features ensure the simplicity, scalability, efficiency and longevity of our THPE. This last implements an iterative enhancement process which is described in this paper: first, a review on thermal enhancement modeling is summarized and our orientation for an extended qualitative modeling is justified. Section 3 explains the THPE's overall algorithm. Important aspects dealing with uncertainty management and decision making are then detailed. In the conclusion section, some of the THPE thermal control experimentation results are displayed, as well as, some theoretical perspectives.

2 Summarized Review and Related Works

Efficient thermal control can be seen as a complex system control (*i.e.,* climate, thermodynamic materials properties, thermal technologies and regulation, human behavior, *etc*.). In fact, considering most of thermal process's influence factors may lead to a significant thermal control improvement. Therefore, predictive and advanced control approaches have been proposed to ensure *smart* thermal control [1-7]. Applied to the thermal context, the predictive control considers socio-economic objectives such as minimizing energy consumption and maximizing thermal comfort [1,2]. It is based on a mathematical thermal control modeling. Therefore, the more detailed and accurate the model parameters are, the more efficient the control would be. However, mathematical model design requires expertise, as well as, detailed and precise quantitative knowledge on buildings' thermal behavior. Advanced control has been applied for 20 years in *smart* thermal control [3]. It is mainly based on Artificial Intelligence (AI) techniques and aims to provide a simple, efficient and adaptive control without requiring detailed mathematical modeling. Indeed, learning techniques are used for system modeling. Two different paradigms can be distinguished: the quantitative one (*i.e.* statistical modeling [4] and AI modeling techniques such as ANNs (Ant Neural Networks) [5], SVMs (Support vector Machines) [6], *etc.)* and the qualitative one (*i.e.,* qualitative rules and expert based modeling [7]). Quantitative control modeling requires input training data which is, usually collected through *onsite* measurements, surveys, and available documentations. Data pre-treatment and post-treatments are, hence, requested in order to improve the model efficiency. Thermal control quantitative learning is obviously a complicated task which requires important computation loads. In fact, mathematical modeling is the hardest one since it requires the biggest amount of setting data and measurements. Statistical modeling is much easier than the mathematical one however it stills not sufficient and flexible for a refined *smart* thermal control. Well learned ANN and SVM models are more appropriate to ensure a refined smart thermal control. They, however, need significant computation loads, as well as, efficient and sufficient training-data. The qualitative formalism allows reducing the complexity of thermal control modeling. It can be less data dependent compared to the quantitative ones (expert knowledge could be sufficient for the *smart* control modeling). Ambiguities and accuracy's lack may affect negatively the qualitative modeling efficiency and longevity for a continuous enhancement purposes. Nevertheless, a qualitative thermal control modeling can be easily adapted for different thermal scales such as buildings and *smart* grids. In order to ensure an efficient, scalable and simple *smart* thermal control, we have applied well-known qualitative enhancement techniques [8-11]. These techniques were proposed a long time ago by Williams [9], Kuipers [9] and others [10,11] in order to improve qualitative modeling efficiency and reduce their ambiguities. A survey is proposed in [11]. Therefore, we propose an Extended Qualitative Model (EQM) for an efficient, scalable and simple *smart* thermal control. Time-related informations, as well as, 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, denoted 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. The approximate reasoning (THPE: THermal Process Enhancement) based on our EQM can, thus, be generalized for various thermal scales and specificities. Furthermore, it does not require any particular setting data and important computation loads.

3 THPE's General Approach

Our *smart* thermal control THPE is inspired from human's increasing abilities when manipulating objects. Let us consider an amateur cyclist who is learning how to efficiently ride his new bicycle. When climbing hills, the cyclist is continually trying to adapt his riding in order to maximize his speed and minimize his effort. For this, he does not know much about his bicycle metal, tires and wheels spoke compositions and measurements. He generally does not know precisely the characteristics of his climbing paths. However, over the time, the cyclist remains able to improve his climbing performances. In fact, the more he climbs, the more his riding performances will get better. Actually, his improvement is only based on simple rules and comparisons over his previous climbing. For instance, the cyclist may know basic riding rules about his bicycle rear wheel cogs: *if climbing is hard then use a bigger cog* and *if you want to go faster then use a smaller one*. Using these simple cog's rules and considering his previous climbing observations, the cyclist displays an approximate reasoning that can be illustrated by the following statements: "*This new hill looks like a previous one that exhausted me by that time. Therefore, to make it less exhausting I should try a bigger cog for this new hill", "I once tried to climb this kind of hills but every time my performances were slow. To go faster, I should use a smaller cog this time"*. Our THPE tries to reproduce the same approximate reasoning. 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 similarly as the cog's rules in the cyclist example. 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 informations of the thermal general behavior. The influences, among parameters and performances, are vaguely identified from thermal general behavior models. Their accuracy is constantly improving through *online* thermal quantitative observations. Similarly as the cyclist memories about his old climbing experiences, keeping track of predate thermal control, as well as, their performances allows recalling them in similar control situations. A Thermal Control Manager (TCM) has 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 controls 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. Fig. 1 displays the THEP's algorithm describing the general approach for a *smart* thermal control based on the EQM and TCM. 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 that need to be reached before occupants show up. Setpoints can, also, be efficiently identified based on an overall aggregation function (*i.e.,* thermal comfort), as well as, thermal indoor and outdoor fluctuations [12,13]. In this paper, we particularly focus on THPE's aspects dealing with reducing uncertainty about buildings' thermal control. Thus, we start by explaining our different approaches used for decreasing uncertainty about the EQM influence approximations. In order to ensure an accurate thermal control, quantitative knowledge is, then, used (step 1 and 2 in Fig. 1). Section 5 deals with uncertainty about the choice of these quantitative information in order to ensure an efficient and accurate thermal control.

THEP (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} (section 5)
    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} (section 5)
      3. Compute CMD^{new} for S^{new} based on the EQM (section 4) 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

Fig. 1. THPE general algorithm

4 Influence Approximations

In order to ensure the THPE weak dependency *w.r.t.* each building's thermal specificities, the EQM applies an event-based representation [14] for the thermal control laws description. This last is more relevant than a classical sampled time representation. It is, also, considered sufficient for the thermal control laws' description since steps and ramps signals are usually used for the thermal regulations. For instance, the EQM considers the thermal control starting time which is useful to improve control delays. For each thermal control law $\mathcal{L}(t)$ we associate a control parameter vector $C=(\Delta t,\Delta p,\Delta y)$. These 3 control events are described by the thermal example showed in Fig. 2 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). CMD refers to the set of control parameter vectors C applied on all building's actuators. Rather than building's thermal profiles, thermal performances are considered in order to ensure the EQM weak dependency *w.r.t.* each building's thermal specificities. Indeed, the performance vector $P=(cost, comfort, flexibility)$ describing thermal energy consumption, stationary thermal comfort and setpoints' achievement delay, ensures building's thermal assessment in our EQM. $PERF$ corresponds, then, to the set of all building's rooms thermal performance vectors P. General thermal behaviors have been studied in order to identify how each control parameter influences the considered thermal performance. Tab. 1 describes, for our EQM, the gradient directions computed over each performance *w.r.t.* each control parameter. Considering gradient directions rather than precise derivative values ensures the EQM's weak dependency *w.r.t.* building's thermal specificities. Hence, the EQM's accuracy may be lacking. However combined to thermal quantitative measurements (CMD^* in Fig. 1), the gradient direction based influences are considered sufficient for the THPE's thermal enhancement. For each thermal 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, $\forall i\in S_C$, and performances p_j, $\forall j\in S_P$, are, respectively, defined in V_i^C and V_j^P. F_{ij} indicates whether the performance j increases (+) or decreases (–) *w.r.t.* variations of the control parameter i. A (0) valued F_{ij} function indicates that the control parameter i has no influence on the performance j. The F_{ij} qualitative gains can, thus, be considered by the EQM for buildings' thermal control enhancement. Tab. 1 displays our EQM's influence functions. Objective and subjective thermal related knowledge is introduced in order to identify influence functions:

Table 1. Gradient direction based influences (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	–	–	+

Objective knowledge corresponds, mainly, to interpretable physical phenomena. These latter can be easily confirmed by studying sign variations of simplified thermal behaviors. 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 Tab. 1, by a constant influence function describing a gradual rule type on $V^C_{\Delta y} \times V^P_{cost}$ such as the greater the heating step amplitude is, the greater the thermal energy consumption would be. Therefore, regardless of buildings thermal specificities, qualitative thermal influence functions can be deduced from simplified physical behaviors (*e.g.,* $F_{\Delta y\ cost}$). Buildings' special features can occasionally be responsible of F_{ij}'s sign variations (*e.g.,* $F_{\Delta t\ cost}$). In this case, simple learning techniques are applied over the TCM's previous attempts 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. Fig. 3 shows some possible shapes of the continuous function relating $c_{\Delta t}$ to p_{cost} measurements. The shape of this function is obtained from the simplified thermal behavior (*i.e.,* in some cases, $F_{\Delta t\ cost}$ displays a maximum. Otherwise it is decreasing for any $c_{\Delta t}$ value). The maximum remains to be identified. Fig. 3'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 launched at time t_1. The $c_{\Delta t}$'s interval for which $cost$ 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 (Heating Ventilation and Air-Conditioning) 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.

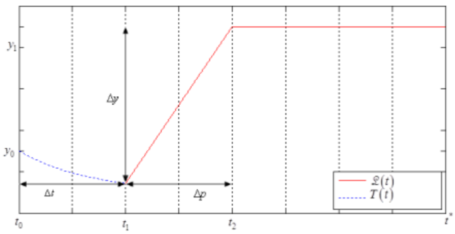

Fig. 2. EQM's Control laws events

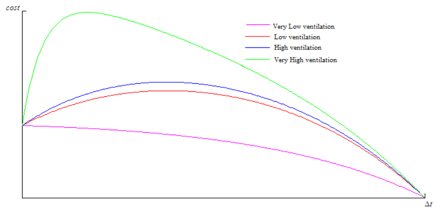

Fig. 3. p_{cost} with regard to $c_{\Delta t}$ variations from different ventilation perspective

Consequently, we propose to use measurements in order to capture, for each building, the $c_{\Delta t} \in V^C_{\Delta t}$ value that entails sign variation in the continuous function (Fig. 3) and finally *online* learn $F_{\Delta t\ cost}$ function. For this, we consider the membership function $\mu_{\Delta t\ cost} : V^C_{\Delta t} \to [0,1]$ which describes the possibility degree that $c_{\Delta t} \in V^C_{\Delta t}$ may correspond to $F_{\Delta t\ cost}$'s sign variation (*i.e.,* a maximum of the continuous function relating Δt to $cost$). Initially, when no information is available, $\mu_{\Delta t\ cost}(c_{\Delta t})$, $\forall c_{\Delta t} \in V^C_{\Delta t}$. This case illustrates the complete ignorance regarding $F_{\Delta t\ cost}$ behavior. $\mu_{\Delta t\ cost}$ is built through *online* thermal quantitative observations. Triplets of $(c_{\Delta t}, p_{cost})$ are ranked according to $c_{\Delta t}$. The qualitative derivative of the continuous function relating $c_{\Delta t}$ to p_{cost} is, then, computed. $F_{\Delta t\ cost}$'s values can, hence, be deduced. Each new relevant thermal attempt $(S^{new}, CMD^{new}, PERF^{new})$ recommended by the THPE (section 5) and stored by the TCM, provides new triplets of $(c_{\Delta t}, p_{cost})$ which enables new $\mu_{\Delta t\ cost}$'s computations. Therefore, the ignorance interval span of $\mu_{\Delta t\ cost}$ decreases since every new qualitative derivative informs about the monotony of the continuous function. When uncertainty is not considered in the qualitative derivative computations, $\mu_{\Delta t\ cost}$'s values belong to the $\{0,1\}$ set instead of the [0,1] interval. Uncertainty about the continuous function variations may either come from thermal disturbance or the technique used for the quantitative observations imprecision management. This kind of uncertainty management is out of this paper scope which is dedicated to discuss general uncertainty aspects in buildings' thermal control enhancement. Ideally, the *online* learning process is over when $\exists! c^*_{\Delta t} \in V^C_{\Delta t}$ such as $\mu_{\Delta t\ cost}(c^*_{\Delta t}) = 1$. The membership function based *online* learning can easily be generalized in order to precisely identify more complicated buildings' thermal dependent influence functions.

Subjective knowledge can also be used in order to reduce uncertainty about buildings thermal control. This knowledge involves occupants' expectations *w.r.t.* building's performances and usages. Preference models have been, then, considered. They contribute, as well, to improve our EQM efficiency. The considered preference models can rather be buildings dependent or independent. For instance, in Tab. 1, $F_{\Delta y\ comfort}$ influence function relating $c_{\Delta y}$ to $p_{comfort}$ measurements, is built from an overall thermal performance model that captures the multidimensional concept of *thermal comfort* [12,13]. $F_{\Delta y\ comfort}$ values can thus be identified considering building's occupants thermal sensations as well as thermal context variations (*i.e.,* humidity and sunshine characteristics). In fact, depending on the thermal context, an increasing ambient temperature may either improve or distract the occupant's thermal sensation. Hence, $F_{\Delta y\ comfort}$. acknowledge sign variations since thermal command law amplitude influence building's ambient temperature. Using thermal comfort standard such as the PPD [15] index is useful to ensure the EQM independency toward buildings' thermal properties. As the PPD formalism is complex and inadequate for control purposes, a MAUT (Multi Attribute Utility Theory) version called CIPPD has been proposed to make it easily interpretable [12,13]. The CIPPD is based on utility functions defined for each thermal comfort attribute (*i.e.,* ambient temperature, humidity, radiant temperature, air speed, *etc.*). Attributes' utilities are then aggregated to compute the comfort performance. For more information about the *thermal comfort* based control enhancement, please refer to our previous works [12,13] where you can find an extended discussion about the *thermal comfort* related issues. Considering the CIPPD's analytic form, $\mathrm{sgn}(d(u_T(T))/dT)$ function, where T refers to the ambient temperature and u_T to its related utility function, provides $F_{\Delta y\ comfort}$. values.

Once the EQM influences are approximated using thermal objective and subjective knowledge, thermal enhancement control can then 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 then give priority to the *comfort* performance optimization, then *flexibility* and last the *cost* performance. Hence, based on the EQM, it becomes possible to recommend control parameters increase/decrease. Step 3 of the THPE (Fig. 1) is, then, as follows: the quantitative information $(S^*, CMD^*, PERF^*) \in TCM$, computed in step 2, provides the most favored prior attempt *w.r.t.* the current situation. Then, the EQM's rules are applied to compute a more likely *better* command law CMD^{new} from CMD^*. The most favored $(S^*, CMD^*, PERF^*) \in TCM$ used to improve the EQM accuracy enhancement is explained in section 5.

5 Quantitative Knowledge Choice

The EQM's approximate reasoning is based on the selection of the quantitative control statement $(S^*, CMD^*, PERF^*) \in TCM$ as explained in Fig. 1. From one hand, $(S^*, CMD^*, PERF^*)$ is chosen such as S^* is as similar as possible to S^{new} (step 1 in Fig. 1), and, from the other hand, $PERF^*$ correspond to prior best realized thermal performances (step 2 in Fig. 1). Three decision criteria have been considered in order to identify the most likely favored previous attempt stored by the *TCM*: ***i.*** The first one is similarity between previous thermal situations S and the new one S^{new}. It allows overcoming non-linearity problems related to thermal controls (step 1 in Fig. 1) since maximizing the similarity allows linear 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'' are. Since thermal situations are only defined by temperature measurements, there are no commensurateness problems in $dist(S',S'')$ definition. ***ii.*** The second criterion considered in TCM's statement evaluation is thermal performance. Obviously, the better the resulting thermal performances $PERF$ are, the more favored the control statement would be. For this, Multi-Criteria Decision Analyses techniques have been deployed. Thus, 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 room's set) and prior thermal control attempt k. These steps are related to the energy manager preference modeling which depends on his energy policy. The preference model may be identified using indirect methods such as Macbeth. 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 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 attempt stored by the TCM. ***iii.*** The last criterion considered for TCM's statement assessment is related to previous enhancement results. In fact, predate thermal controls which have led to thermal enhancement failures are disadvantaged in the future TCM's element evaluations. Therefore, we associate a set Bad^k to each $(S^k, CMD^k, PERF^k) \in TCM$. Bad^k gathers prior thermal controls that were computed from $(S^k, CMD^k, PERF^k)$ and led to thermal performance decreases. Considering these 3 criteria, an overall score $score^k$ (1) can be computed for each TCM's stored control in a limited neighborhood of S^{new} in order to satisfy the thermal process linear behavior expected property:

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

The favored quantitative information $(S^*, CMD^*, PERF^*) \in TCM$ used for our EQM enrichment (step 3 in Fig. 1) satisfies $score^* \geq score^k$, $\forall (S^k, CMD^k, PERF^k) \in TCM$. $(S^*, CMD^*, PERF^*)$ is, then, used by the EQM in order to compute more accurate enhancement thermal control.

6 Conclusion and Some Experimental Results

In our previous work, we have proposed an approach allowing the computation of the most relevant target values (*i.e.*, setpoints) to be provided to the energy control system in order to improve the thermal sensation and reduce thermal energy consumption [12,13] This paper completes our approach by answering the question how to efficiently reach these setpoints without using any quantitative model and important computation loads to precisely identify each buildings thermal regulation system. Our iterative approach THPE 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. Our THPE has been evaluated on a simulated building area. It ensures a quite quick and stable convergence to an *optimum* (based on the considered preference model) thermal control for every new thermal situation. In fact, a few enhancement iterations (less than 10 in most evaluation tests) are needed in order to find the *optimum* thermal control for any new thermal situation. For instance, Fig. 4 shows one room thermal enhancement process. Day 0 matches the TCM initial previous thermal control observation. Day 1 corresponds, in the same room, to the thermal profile computed for a new thermal situation based on Day 0's posteriori available quantitative information. The EQM recommendations over Day 0's control ensures 14.5% of thermal energy consumption decrease. Control enhancements are iteratively computed for the same thermal situation as Day 1 (from Day 2 to Day 5). In Fig. 4, the THPE's enhancement converges in 5 iterations where Day 5 displays the thermal profile that ensures the *optimum* thermal performances for the considered thermal situation. Our experimentations reveal about 7 to 31% for one room thermal performance enhancement and 12 to 24% for several rooms thermal enhancement. Average enhancement ensured by the THPE is evaluated to 16%. How the THPE can bypass frequent thermal control deployment issues such as quantitative data availability, it can be considered as an outstanding point compared to the existent thermal control solutions. Any comparison becomes, thus, unbalanced because of the different application conditions. Trying to operate an MPC in few days on a completely new building is not conceivable. It goes the same when asking the THPE for the same efficiency as an MPC based control. Yet, perspectives remain possible to improve our THPE efficiency. Uncertainty management in influence functions can be improved by using continuous scales membership functions. 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 THPE's convergence to a global *optimum* rather than a local one.

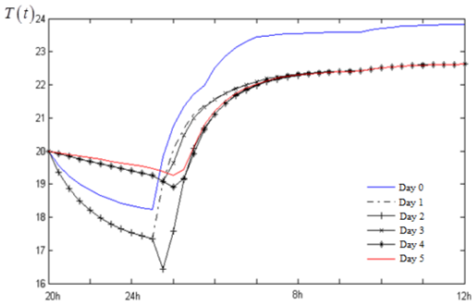

Fig. 4. One room thermal enhancement

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