Comfort as a multidimensional preference model for energy efficiency control issues

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Abstract. The incessant need for energy has raised its cost to unexpected heights. In response to this situation, many projects have been started in order to save energy. In this context, RIDER project tries to develop a weak system dependency of energy management framework which could be applied for different systems. Particularly, our RIDER Decision Support System (DSS) focuses on proposing generic control rules and optimization techniques for energy management systems. Therefore, the DSS aims to compute the most relevant target values (i.e., setpoints) to be provided to the energy control system and then, improving thermal comfort sensation or reducing energy costs. Literature proposes reusable system independent statistical models for thermal comfort. However, they are not easily interpretable in terms of a preference model which makes control not intuitive and tractable. Since thermal comfort is a subjective multidimensional concept, an interpretable and reusable preference model is introduced in this paper. Multi Attribute Utility Theory (MAUT) is used for this.

Keywords: Thermal comfort, preference model, energy control, MAUT, Choquet integral.

1 Problematic Introduction

Total building energy consumption accounts for about 40% of total energy demand and more than one half is used for space conditioning: heating, cooling, and ventilation [1] [2] [3]. In the EU, about 57% of total energy consumption is used for space heating, 25% for domestic hot water, and 11% for electricity [4]. In response to this situation, many projects have been started in order to save energy. Recent studies have investigated efficient building control in order to find strategies that provide a comfortable environment from thermal, and indoor-air quality points of views, and minimize energy consumption at the same time [5]. Nevertheless, these optimization systems are strongly dependent on the energy management framework and cannot be

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applied for other systems. Indeed, they are conceived by the energy manager depending on one building characteristics. So, its associated optimization routines are directly implemented on its control system and cannot be reused for further energy management. Additionally, these optimization routines are not supposed to be interpreted by human operators since they are integrated in regulation loops which made them necessarily dependent on the SCADA system (supervisory control and data acquisition). In order to solve this problem and satisfy the weak energy system dependency which is required by the RIDER project, control rules should neither be too specific nor integrated in control loops. They must rather be a high level supervision rules which can be suggested to the energy manager. That's why; we propose that the RIDER DSS core functionalities should rather provide qualitative recommendations such as suggesting the most relevant target values to the energy control system. This approach ensures, the control rules interpretability, as well as, the weak dependency of the DSS w.r.t. the energy system and its control.

This research is part of the RIDER project and deals only with its optimization aspects. In this paper, we focus on a specific optimization aspect based on human's thermal sensation. In fact, the notion of comfort is subjective and multidimensional. Subjectivity entails that comfort cannot be modeled in a deterministic way and its multidimensionality comes from the fact that many variables can be considered in its definition: temperature but also hygrometry, radiant temperature and air velocity. These remarks explain why providing efficient energy management for optimal comfort may be considered as a multicriteria decision-making process in uncertain environment, and must be modeled as such [6].

The next sections discuss about the modeling and the implementation of an original thermal comfort function and formalize, as well, some RIDER optimization problem based on the aforementioned comfort function.

This paper is organized as follows. Section 2 discusses about most common thermal comfort models and their relevance when they are used in optimization process. It explains our choice to have a model which interprets the comfort statistical model on the MAUT framework. Section 3 summarizes Labreuche's method to identify our thermal comfort model, the way that this method was applied and extended to build a comfort overall utility function in our complex context, and finally shows the usefulness of this new formalization to infer comfort control rules. Finally, section 4 formulates some control problems based on the new thermal comfort preference model.

2 Optimization and comfort

Even when no malfunctioning is detected in a heating system, *i.e.*, temperature values in a building match their setpoints, two users may be more or less tolerant with regard to the setpoint variations and thus not equally satisfied. It can be explained by the more or less tolerant user's requirements are but also by other parameters than temperature that may differ from one situation to another and then contribute to different thermal sensation. This illustrates that thermal comfort (and not only temperature) should be the variable to be controlled by the RIDER DSS in order to ensure building

occupants' satisfaction. However, comfort is a complex and subjective concept that cannot be modeled as a deterministic variable. That's why, in literature, the most well-known thermal comfort is based upon a statistical approach [7] [8].

2.1 Thermal comfort model overview

2.1.1 Comfort as a statistical model

The Predicted Mean Vote *PMV* [7] is the most used statistical thermal comfort index. It defines the mean thermal sensation vote on a standard 7 level scale from a group of approximately1300 persons. It is written as a function of 4 thermal environmental variables: air temperature *Ta*, air humidity *Hy*, air velocity *Va*, and mean radiant temperature *Tr*; and 2 human parameters: metabolic rate *Me* and cloth index *Ci*. The *PPD* (Predicted Percentage Dissatisfied) index is based on the *PMV* one and indicates the percentage of thermal dissatisfied persons. Both *PMV* and *PPD* indexes have been used since 1995 by the NF EN ISO 7730 standard to describe ergonomics of thermal environments [8].

Such a thermal comfort representation verifies the RIDER DSS weak dependency constraint from one hand, and captures the inherent subjectivity and uncertainty related to thermal sensation from the other hand. The statistical based thermal comfort modeling is the result of a sample-ballot which makes it reusable for various application contexts. Whereas comfort is intuitively related to a preference model, the formalism in [7] and [8] is far away from any classical preference modeling framework. *PMV* and *PPD* indexes are considered as if they were outputs of any behavioral model associated to a physical process. In particular, interactions among comfort attributes are considered as if they were physical ones which is not the case. The monotony of *PMV* and *PPD* with regard to attributes variations, is not obvious and can only be numerically computed. As a consequence, interpreting such a model to support control rules design for a human operator is not so intuitive.

2.1.2 Comfort as a preferential model

The representation of preferences is a central topic in decision-making and measurement theory [9]. Usually, it amounts to find a real-valued overall utility function U such that for any pair of alternatives $x, x' \in X$ where X is a set of alternatives, $x \succeq x'$ (x is preferred to x') *iff* $U(x) \geq U(x')$. When alternatives are N-dimensional (attribute $i \in N$ takes its values in X_i), *i.e.*, $X = \prod_{i=1}^{n} X_i$, a widely studied model is the decomposable model of Krantz et al. [10], where U has the form $U(x_1,..,x_n) = g(u_1(x_1),..,u_n(x_n))$ where u_i are real-valued functions. Assuming that $\succeq$ is a weak order on X, it is known that a representation with g being strictly increasing can be found *iff* $\succeq$ satisfies independence and X is separable [9]. The MAUT [11][12] is based upon the utility theory which is a systematic approach to quantify individual preferences. Utility theory consists in interpreting any measurement as a satisfaction degree in [0,1] where 0 is related to the worst alternative and 1 to the best one. Measurements are

thus made commensurate and interpretable. In this way, a utility $u_i(x_i)$ is attached to each measurement x_i.

Indirect interviewing methods such as MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique) are generally applied to identify attribute elementary functions $u_i(x_i)$ in a weighted average aggregation model. However, when aggregation operators do not fulfill the weak difference independence property then constructing elementary utilities functions is more complicated [16]. Indeed, this property allows building the value function on attribute i by asking questions directly regarding the preference of the decision maker on the attribute value range X_i (independently of other attributes values) rather than from questions regarding options in X. An extension of MACBETH for a Choquet integral aggregation function that respect weak difference dependence has been proposed in [13] [14].

When comfort can be written under the decomposable form $U(Ta,...,Me) = g(u_{Ta}(Ta),...,u_{Me}(Me))$ it makes thermal sensation more interpretable w.r.t attributes variations and avoids the coexistence of antagonist behavioral rules. For instance, comfort may be improved when humidity increases for one given ambient temperature whereas it can be disturbed by an increasing humidity for another ambient temperature. The coexistence of such behavioral rules makes difficult for the energy manager to directly imagine attribute variations in order to control the energy system. Whereas co-monotony of comfort U and u_{Hy} holds everywhere in X_{Hy}. Then, identifying the elementary utility functions u_i would greatly facilitate the design of control rules. Moreover, in the real thermal comfort perception, there is no physical correlation between attributes. Interactions between attributes should rather be considered as preferential interactions related to criteria associated to attributes [15] [16]. Fuzzy integrals provide adequate models to capture such interactions. It is then obvious that a preferential model of thermal comfort would be more appropriate for semantic reasons.

2.1.3 Discussion

Let us now introduce these models in optimization issues. Optimization problem (1) and its dual (2) —where $Cost(\delta Ta, \delta Hy, \delta Tr, \delta Va, \delta Ci, \delta Me)$ function evaluates the cost of the attributes variations $(\delta Ta, \delta Hy, \delta Tr, \delta Va, \delta Ci, \delta Me)$ and PPD^* (resp. C^*) is a comfort setpoint (resp. a budget threshold)— formalize efficient comfort improvement issues.

$$\begin{cases} \min Cost(\delta Ta, \delta Hy, \delta Tr, \delta Va, \delta Ci, \delta Me) \\ PPD(Ta+\delta Ta, Hy+\delta Hy, Tr+\delta Tr, \\ Va+\delta Va, Ci+\delta Ci, Me+\delta Me) \le PPD^* \end{cases} \quad (1)$$

$$\begin{cases} \max 100 - PPD(Ta+\delta Ta, Hy+\delta Hy, \\ Tr+\delta Tr, Va+\delta Va, Ci+\delta Ci, Me+\delta Me) \\ Cost(\delta Ta, \delta Hy, \delta Tr, \delta Va, \delta Ci, \delta Me) \le C^* \end{cases} \quad (2)$$

Let $\vec{\nabla} PPD$ the gradient when $PPD(Ta,...,Me) = PPD^*$. It provides attributes that their local variations impact the most significantly the comfort variation (maximal component of $\vec{\nabla} PPD$). However, there are some practical and computational draw-

backs to this formulation. First, the gradient is generally not of common sense for the energy manager to be use in optimization process. Then, there is no information regarding the neighborhood in which this result is valid: maximal component of $\vec{\nabla} PPD$ may change rapidly *i.e.* it depends on non linearity of PPD and this notion is meaningless for the energy manager. Finally, we cannot a priori know whether we have to increase or decrease an attribute value to improve PPD . It necessitates computing the derivative. It depends on Ta, Hy, Tr, Va, Ci, Me attribute values and the monotony of PPD relatively to these attributes, which is not easily understandable for the energy manager. However, a preferential based thermal comfort modeling solves the aforementioned drawbacks thanks to the co-monotony between utility functions u_i and thermal comfort overall evaluation U , and offers as well a more relevant control system for thermal comfort attributes.

In order to ensure the RIDER DSS weak dependency, the thermal comfort model has also to fulfill this condition. The statistical thermal comfort modeling satisfies already the weak dependency condition and can be applied for different system whereas the preferential thermal comfort modeling does not always stratify this condition. It depends on the way with which utility functions u_i were identified *i.e.* utility functions should result from statistical techniques like in [7] and [8] which would roughly make the interviewing method more complex.

So, to grant to the comfort preferential based model the ability to be system independent without having to proceed by the statistical way, we propose to identify utility functions from the existent statistical model PPD . Labreuche has proposed an original approach to compute both the utilities and the aggregated overall utility function $U(x_1,..,x_n)$ when U is a Choquet integral without any commensurateness assumption [17]. It is important to highlight that using a Choquet integral facilitates optimization problem solving ((1) and (2)) thanks to its linearity by simplex. Next section describes the Choquet integral and Labreuche's method to identify utility functions and the Choquet integral parameters.

2.2 Measurements overall utility without commensurateness hypothesis

2.3.1 The Choquet integral

The Choquet integral family provides adequate models to capture decisional behaviors when there are preferential interactions between criteria. They enable accommodating both the relative importance of each criterion and the interactions among them [18][19]. In our preference model, an interaction occurs between any two criteria once they need to be satisfied simultaneously (i.e., positive synergy) or when their simultaneous satisfaction is seen as a redundancy (negative synergy).

$$U = C_\mu(u_1, u_2, ..., u_n) = \sum_{i=1}^{n} (u_{(i)} - u_{(i-1)}).\mu(A_{(i)}) = \sum_{i=1}^{n} \Delta\mu_{(i)}.u_{(i)} \quad (3)$$

U , in (3), is the aggregate utility of the elementary utility profile $\vec{u} = (u_1, ..., u_n)$ (to simplify u_i abusively denotes $u_i(x_i)$ when no misinterpretation is possible) where

$\mu : 2^C \to [0,1]$ is a fuzzy measure on the subsets of criteria in C; (.) indicates a permutation, such that the elementary utilities $u_{(.)}$ are ranked: $0 \le u_{(1)} \le \ldots \le u_{(n)} \le 1$ and $A^k_{(i)} = \{c_{(i)},..,c_{(n)}\}$. This expression can also be rewritten as in the last part of (3) where $\Delta\mu_{(i)} = \mu_{(i)} - \mu_{(i+1)}$ and $\mu_{(i)} = \mu(A_{(i)})$, $\mu_{(n+1)} = 0$.

Note that a simplex $H_{(.)} = \{\vec{u} \in [0,1]^n / 0 \le u_{(1)} \le \ldots \le u_{(n)} \le 1\}$ corresponds to the ranking (.), where the Choquet integral assumes a linear expression. Such a remark proves that optimization problems that involve a Choquet integral can be solved with linear programming techniques within simplexes.

2.3.2 Construction of Choquet integral and elementary utilities without any commensurateness assumption

Since we want to represent *PPD* with the decomposable model of Krantz, weak separability property has to be first verified. A preference relation $\succeq$ is said weak separable *iff*, it verifies (4) for every attribute $i \in N$ where *N* denotes the attribute set, $x_i, x'_i \in X_i$ two possible values of i, and $y_{N\setminus i}, y'_{N\setminus i} \in \prod_{j \ne i}^{n} X_j$ two possible alternatives described for $\forall k \in N$ and $k \ne i$.

$$\forall x_i, x'_i, y_{N\setminus i}, y'_{N\setminus i},\ \left(x_i, y_{N\setminus i}\right) \succeq \left(x'_i, y_{N\setminus i}\right) \Leftrightarrow \left(x_i, y'_{N\setminus i}\right) \succeq \left(x'_i, y'_{N\setminus i}\right) \quad (4)$$

Labreuche [17] supposes that the weak separability property is verified for the overall utility function *U* (*PPD* in our case) and suggests a method to check commensurateness among attributes i and k. For this, he proposes to analyze the gradient function related to x_i w.r.t x_k variations. It returns on studying the function $f_i : x_k \mapsto U(x_i + \varepsilon, x_{N\setminus i}) - U(x)$ where $\varepsilon > 0$. If f_i is a constant function, then there is no interaction between attributes i and k (it means that even when there is a ranking change between utilities related to i and k their "weights" in (3) do not change in the new simplex). And, thus, attributes i and k do not interact. Otherwise, if f_i is not a constant function, then attributes i and k interact with each other (the "weight" in (3) depends on their ranking). In this case, i and k are considered as commensurate and it is possible, then to compute the value $x^*_k \in X_k$ for the attribute k where $u_k(x^*_k) = u_i(x_i)$ [17]. At the end of this step, subsets of commensurate attributes $S_j \subseteq N$ are constructed, where $\bigcup_j S_j = N$ and $\forall i,k \in S_j$, i and k are commensurate.

Once S_j are identified, the utility functions u_i and capacities μ_j can be computed. According to [20], u_i cannot be built from one attribute regardless to the other ones. u_i's construction in [17] is thus based on the overall utility U. [17] supposes that U is continuous and all u_i functions are strictly increasing over $\mathbb{R}$ ($\forall i, X_i = \mathbb{R}$ in [17]). In

order to build u_i and μ two reference vectors $\mathbf{O}_{S_j}, \mathbf{G}_{S_j} \in \prod_{k \in S_j} X_k$ should be computed for each attribute subset S_j. They refer respectively to an unacceptable (Null) situation level and a Good situation level. For vectors $\mathbf{O}_{S_j}$ (resp. $\mathbf{G}_{S_j}$), the first attribute value x_l^O (resp. x_l^G) is chosen by the decision maker and the others $x_{k \neq l}^O$ (resp. $x_{k \neq l}^G$) are computed such as $u_{k \neq l}\left(x_{k \neq l}^O\right) = u_l\left(x_l^O\right)$ (resp. $u_{k \neq l}\left(x_{k \neq l}^G\right) = u_l\left(x_l^G\right)$) for $\forall k \in S_j$ and $k \neq l$. To make sure that $\mathbf{G}_{S_j}$ corresponds to a better situation than $\mathbf{O}_{S_j}$, $x_{k \neq l}^G$ must be preferred to $x_{k \neq l}^O$.

Based on the identified reference vectors, an affine utility function υ_i is defined by (5), where $\upsilon_i\left(x_i^O\right) = 0$, $\upsilon_i\left(x_i^G\right) = 1$, $\mathbf{O}_A$ is the restriction of $\mathbf{O}_N = \left(x_1^O, ..., x_n^O\right)$ to $A \subset N$ (resp. $\mathbf{G}_A$ is the restriction of $\mathbf{G}_N = \left(x_1^G, ..., x_n^G\right)$ to $A \subset N$).

$$\forall x_i \in \left[x_i^O, x_i^G\right], \upsilon_i(x_i) = \frac{U(x_i, \mathbf{O}_{N \setminus i}) - U(\mathbf{O}_N)}{U(x_i^G, \mathbf{O}_{N \setminus i}) - U(\mathbf{O}_N)} \tag{5}$$

Since several solutions for $\mathbf{O}_{S_j}$ and $\mathbf{G}_{S_j}$ may be envisaged, a normalization condition is required: when $\sum_{S_j}\left(U(\mathbf{G}_{S_j}, \mathbf{O}_{N \setminus S_j}) - U(\mathbf{O}_N)\right) = 1$ is checked, then normalized utilities u_i and normalized capacities μ_{S_j} are respectively (6) and (7):

$$u_i(x_i) = \upsilon_i(x_i) + U(\mathbf{O}_N) \quad (6) \qquad \forall A \subset S_j, \mu_{S_j}(A) = U(\mathbf{G}_A, \mathbf{O}_{N \setminus A}) - U(\mathbf{O}_N) \quad (7)$$

Finally, the Choquet integral (see (3)) that represents the overall utility *U* of the normalized utilities u_i based upon the generalized capacity μ given by (8) is achieved:

$$\forall A \subset N, \mu(A) = \sum_{S_j}\left(\mu_{S_j}(A \cap S_j)\right) \tag{8}$$

3 Decomposable form of the aggregation model of comfort

Interactions between $Ta, Hy, Tr, Va, Ci,$ and Me are preference interactions rather than physical correlations [15]. In fact, preferences are perfect to model human perception or opinion about comfort which is a subjective concept and cannot be treated like a physical process output as in [8]. Choquet integral is a relevant solution to model preference interactions among thermal comfort attributes and confers to the comfort aggregated concept its semantic interpretability. Also, the simplex piecewise linearity of Choquet integral facilitates optimization processes.

So, in order to solve problems described by (1) and (2), approximating the *PPD* with a Choquet integral, is then of interest. It first reduces the *PPD* complexity by giving the possibility to have a linear formulation. Second, it allows easy prediction of *PPD* variation with regards to one attribute fluctuation since we have elementary utility functions.

In order to simplify the Choquet comfort modeling, we suppose that people hosted by a same building have almost the same activity level and are dressed pretty much the same depending on seasons. Considering those assumptions, *Ci* and *Me* attributes can be removed from the model variables (they are seen as constant parameters instead of variables). Thus, depending on seasons and the activity nature of a building, both *Ci* and *Me* are evaluated by average values i.e., $Me = 1.2\,met$ for average administrative employees and $Ci = 0.7\,clo$ for a shirt/pant dressing sample [8].

3.1 Weak separability assumption and Choquet integral-based local model

In order to write the *PPD* function as an overall utility function, it's necessary to check, first, the weak separability property among its attributes $Ta, Hy, Tr,$ and Va which, intuitively, seems to be not the case. Here is a counterexample of the weak separability non-satisfaction computed for the vector (Ta, Hy, Tr, Va), $(23,50,23,0.2) \prec (25,50,23,0.2)$ however $(23,100,23,0.2) \nprec (25,100,23,0.2)$. Therefore, we can say that $PPD(Ta, Hy, Tr, Va)$ defined for $Ta \in [10,30°]$, $Tr \in [10,40°]$, $Hy \in [0,100\%]$, and $Va \in [0,\ 1m/s]$ [8] is not a weak separable function. Second, the monotony assumption of Labreuche's construction must be checked. Again, intuitively, this assumption cannot be proved for the considered areas of $Ta, Hy, Tr,$ and Va. It is obvious that an increasing temperature is appreciated until an upper threshold. Above this threshold, people get hot and their thermal sensation progressively decreases. This fact implies that the elementary utility function of the ambient temperature $u_{\mathrm{Ta}} : [10,30°] \to [0,1]$ has at least one monotony change.

Fig., 1 and 2, illustrate respectively the *PPD* curve for ($Tr = 23°$, $Hy = 25\%$, $Me = 1.2\,met$, $Ci = 0.7\,clo$, $Ta \in [10,30°]$ and $Va \in [0,1m/s]$) and ($Tr = 23°$, $Hy \in [0,100\%]$, $Me = 1.2\,met$, $Ci = 0.7\,clo$, $Ta \in [10,30°]$ and $Va = 0.2\,m/s$). Isotemperature curves of both figures have the same shape for respectively all *Va* and *Hy* values. So, we can realize that the minimal *PPD* is reached for slightly different *Ta* values, which means that the weak separability property is not verified in the considered *PPD* domain. Fig., 1 and 2, show, also, that *PPD* function has two different monotonies w.r.t. *Ta* values which means that u_{Ta} cannot be considered as strictly increasing for $Ta \in [10,30°]$. Since none of the two required assumptions is verified, we cannot build an overall Choquet integral for all *PPD* attributes domains. However, these assumptions can be checked for different local domains and, then, a Choquet integral can be computed for each of these domains. Based on this, we have to identify domains in which the shape of the *PPD* function has the same monotony and verifies, as well, the weak separability property i.e., according to figures 1 and 2, for $Ta \in [25,30°]$, we have both assumptions verified. So it is possible to compute a Choquet integral defined locally for $Ta \in [25,30°]$. Hence, the *PPD* function can lo-

cally be approximated by a Choquet integral. This technique allows the computation of local preference models for the thermal comfort. It means that depending on situations, attribute utility functions change. In fact, one attribute influence on the thermal comfort becomes more or less important depending on Ta value range.

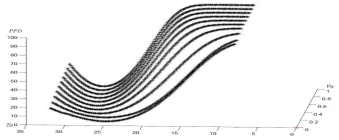

Fig. 1. $PPD(Ta,Va)$

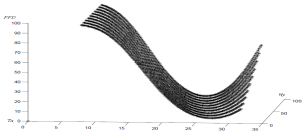

Fig. 2. $PPD(Ta,Hy)$

3.2 A fuzzy inference system to estimate comfort

In practice, the PPD index can only be controlled through $Ta, Hy,$ and Va attributes where Va is equivalent to a room airflow of the heating exchanger. So, more specifically, we need to associate elementary utility functions to these attributes to simplify control issues. Besides, Tr is beyond control except if we close the shutters! Furthermore, it can be checked that interactions with Tr are not preferential ones. Tr interactions are related to physical relationships with Ta which are not semantically considered by the Choquet integral model and do not correspond to the Labreuche's construction. That's why, in order to simplify our model and, also, reduce the complexity of the identification of local validity domains, we decide to remove Tr from our PPD approximation. Therefore, a Choquet integral is computed for a fixed Tr in tridimensional local domains of validity of $Ta, Hy,$ and Va . In this case, a fuzzy interpolation for Tr is proposed to consider all Tr range.

Fig. 3 shows the way the 5 different tridimensional model $U_{\text{comfort}}^{\text{Tr}=x_{\text{Tr}}}$ cover all Tr range. A local Choquet integral model approximates the PPD function for these fixed values of Tr: 15, 20, 23, 25 and 30°. Then, $U_{\text{comfort}}^{\text{Tr}=x_{\text{Tr}}}$ approximates the PPD function only in its associated valid local domain. Comfort can finally be computed for any Tr value thanks to an interpolation between two local models as proposed by the triangular membership functions in figure 3.

In all computed local approximations, $Ta, Hy,$ and Va have been checked as commensurate which means that utilities and capacity approximations are all based on two reference vectors $\mathbf{O}_{S_1}$ and $\mathbf{G}_{S_1}$ associated to the unique commensurate subset $S_1 = \{Ta, Hy, Va\}$. According to [17], the Choquet integral is unique when commensurate subsets are composed with the coalition of all attributes. In this case, it can be checked that all our local constructions are unique [17]. Utilities and capacity functions require to be normalized. Because there is only one commensurate subset, checking the normalization condition $\alpha.\left(PPD\left(\mathbf{G}_{S_1}\right) - PPD\left(\mathbf{O}_{S_1}\right)\right) = 1$ is easy but must be verified in each local domain.

Average approximation errors between the local Choquet approximation and the *PPD* function are computed based on 9261 different simulations and it never exceeds 9.8% on $Ta \times Hy \times Va$ valid domains. The next section describes how these 5 tridimensional comfort models can be useful to control one building thermal comfort.

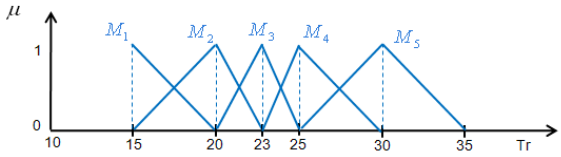

Fig. 3. Five tridimensional $U_{comfort}^{Tr=x_{Tr}}$ based interpolation

3.3 Interpretable control rules

The computation of these local Choquet integrals with [16] implies that we have simultaneously built utility functions for each attribute u_{Ta}, u_{Hy}, and u_{Va} in each domain of validity. These last can then be used in order to build control rules. Thanks to the utility functions, from each local Choquet integral model, the influence of each attribute variation $\delta Ta, \delta Hy$, and δVa on the $U_{\text{comfort}}^{\text{Tr}=x_{\text{Tr}}}$ monotony can be computed. Of course, these influences models are not as precise as we hoped for because they result from the interpolation of two local Choquet integral models; but they still useful to give helpful control recommendations. In fact, the non-existence of a unique overall Choquet integral defined for the whole *PPD* domain inhibits all comparison between utilities in two different local domains. However, it is not such a problematic thing because, for each local domain, we are yet able to identify its valid rules i.e., (9) is an identified thermal comfort control rule for the local model M3 (fig. 3). It models the attribute *Hy* influence upon $U_{\text{comfort}}^{\text{Tr}=23^\circ}$ for the local domain M3. Then this rule can be formulated as a recommendation when environmental conditions satisfy the local domain M3. The "gains" related to these relationships are the $\Delta\mu_{(i)}$ Choquet integral parameters (3) for M3. Hence, the energy manager knows the negative or positive influence of any attribute upon comfort function in any domain, the polyhedrons in which this influence is valid, and the expected impact from an attribute variation. It allows enunciating control rules such as (9).

$$\begin{aligned} &\text{M}_3 : Ta \in [22,28], Hy \in [50,100], \text{and } Va \in [0.25,1] \\ &\textit{if } Hy \nearrow \text{ then } U_{comfort} \searrow \text{ because } u_{Hy} \searrow \text{ and } \delta U_{comfort} = \Delta\mu_{Hy}^{[22,28]\times[50,100]\times[0.25,1]}.\delta Hy \end{aligned} \quad (9)$$

Hence, thanks to the *PPD* approximation by local Choquet integrals, we obtain a set of rules for the thermal comfort control. These rules can directly be applied by the energy manager as suggested just above because they are interpretable rules in term of satisfaction degrees (like comfort itself) which is part of our work objectives. The Choquet integral based models can also be included in optimization problems to effi-

ciently improve comfort or reduce energy costs automatically as it is explained in the next section. This can be achieved thanks to the Choquet integral linearity by simplex.

4 Some control problems based on the piecewise Choquet integral

The model of comfort is now built in the control of the energy system of a building floor. Let us suppose that the control variables are ambient temperature and airflow of all the offices at this floor. There is a General Air Treatment (GAT) —a central heating exchanger—for the whole building and additional individual heating exchangers in the offices. Basic control functions are already implemented in the GAT.

In RIDER DSS, comfort appears as an overall performance of the control problem. It must help the energy manager to satisfy each individual comfort expectation with a minimal cost. Indeed, persons do not have the same expectations w.r.t thermal comfort, on one hand, and one office heat loss depends on its exposure to sunlight, and its neighboring offices isolation characteristics, on the other hand.

RIDER DSS supports the energy manager to manage significantly different temperature setpoints in each office at the floor in order to warranty the comfort levels and minimize as well the energy cost. Then, in order to satisfy both requirements: cost and comfort constraints, RIDER DSS aims to compute adequate setpoints to be provided to the GAT control system. In this paper, we consider that RIDER DSS manages only the energy system performances (utilities related to measurements) without worrying about the way these performances are achieved (GAT control). RIDER DSS aims to prove that reasoning using an aggregated comfort objective function already provides substantial savings. Let us consider some tractable issues by RIDER DSS:

- **Control**. The control issue may be used to adjust the thermal sensation of an unsatisfied officer and whenever any disturbance distracts from the comfort expectation;
- **Adaption**. Thermal sensation is not the same in the north sided offices of the building and the south sided ones. Furthermore the sunlight exposure varies every day and during the day;
- **Anticipation**. Season changes and occupation rates, are proceeding to phenomena that directly impact energy management.

For instance, (10) is a formalization of a simple control problem based on the comfort preference model F that has been identified from the *PPD* model in this paper. This formalization aims to control variables Ta and Va (the offices airflow) in order to improve the thermal sensation of an unsatisfied office occupant $comfort(k)$ without decreasing the comfort of its neighboring offices k' when $Ta(k)$ and $Va(k)$ change.

$$\begin{cases} \min \delta Ta(k) \\ Comfort(k) = F(Ta + \delta Ta(k), Hy(k), Tr(k), Va + \delta Va(k), Ci, Me) = Comfort^* \\ \delta Ta(k) \geq 0 \\ \forall k' \neq k, Comfort(k') \geq setpoint(k') \end{cases} \tag{10}$$

Because F has been approximated with Choquet integrals, this optimization problem can be locally linearized and, so, becomes an easily tractable problem [21]. Furthermore, the gain between comfort degree and δTa or δVa variations is locally a constant computed with Ta and Va related utility functions and also the Choquet integral parameters in the simplex search space. This gain value makes the improvement interpretable for control purposes. Finally, domains of validity of the Choquet integral based approximations provide the necessary bounds to reason with a constant gain.

Similarly, the adaptation and anticipation problems can be easily formalized as the control one and their resolution are also simplified thanks to the local linearity of the Choquet integral expression.

5 Conclusion

This work focuses on proposing generic optimization techniques for energy management systems based on a thermal comfort preference model. It explains why and how associating comfort to a MAUT preference model for energy management issues. The introduced thermal comfort model can be easily generalized for different building occupants and simplifies the energy control issues. In fact, thanks to the MAUT, the interpretation of attributes influences on the thermal sensation in term of utility functions makes the multidimensional comfort control process more tractable. The introduction of MAUT techniques in energy control completely shifts the energy control paradigm. For example, the aggregated model for comfort allows designing new lower temperature setpoints that could not be envisaged even in advanced multivariable control techniques. Indeed, relationships between attributes are preferential interactions and not physical influences: each attribute can be controlled independently but any change of an attribute entails a variation of its local utility that may have consequences on the comfort overall utility. RIDER aims to prove that reasoning using an aggregated comfort objective function provides substantial savings. Within the MAUT, it can reasonably be imagined that temperature setpoints of a building could be decreased from one to two degrees. It represents a substantial economic gain that is probably much more significant than any optimization of the energy manager control system. Furthermore, the control recommendations resulting from this model are obviously transferable to any energy facilities.

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