

A Fuzzy Concept for Climate Management in Preventive Conservation

An Approach to Define and Manage Climate Setpoints using Fuzzy Decision Making

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Abstract — Especially for air conditioning tasks with applications in the area of preventive conservation, requirements can only be described by using vague and incomplete information. In this field of application a fuzzy formulation, which considers stationary, dynamical and economy demands of climate values, turned out to be appropriate. The presented paper describes an unifying approach of formulating fuzzy setpoints as well as using fuzzy decision making, in order to develop a automated climate management system for the best possible preventive conservation.

Keywords - setpoint optimization; fuzzy decision making; process management system; preventive conservation

I. INTRODUCTION

Climate describes the state of physical values of an ambiance, mostly of the air. The automation task is to control these values in an effective way, so that they are stabilized in defined climate goals. Climate values are classified into a thermal and non-thermal group. The values concerning the non-thermal group are mainly those, which describe a local concentration of substances, for example the concentration of carbon dioxide. These values mostly represent measures of pollution. They originate from indoor sources and the goal is to reduce their concentration to an accepted limit. Usually the only way to fulfill this demand is to change air volumes with the environment using a ventilation system. [1]

As opposed to this, thermal values (we take the focus on temperature ϑ and relative humidity φ) should not be reduced to a limiting threshold, they have to reach a specified setpoint with an allowed deviation. The aim of keeping these values in a specified range is established by demands of people, caused by aspects of comfort and health.

It is an important fact that climate goals are usually formulated not crisp, but fuzzy. Looking into standards (for this ISO 7730, [2]) only vague parameters define specifications like the predicted mean vote (PMV-Index) and the predicted percentage of dissatisfied (PPD-Index). Hence, in the area of air conditioning and climate management there are only rough values of setpoints (or ranges of setpoints) available. That is

why climatic requirements are often described linguistically and are provided with lack of knowledge [3]. These characteristics leads to the application of Zadeh's fuzzy theory [4], using fuzzy numbers and intervals [5] to formulate setpoints and evaluate controlled variables [6], [7] by creating a membership function (like in figure 1).

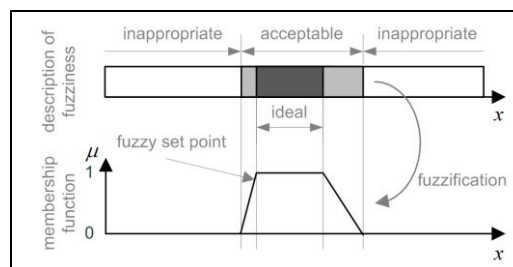


Figure 1. Fuzzification of a vaguely known setpoint

Conventional applications of air conditioning already use intervals of setpoints in order to realize energy-efficient operations and to reduce operation costs. Furthermore, state of the art concepts use theory of fuzzy decision making in order to generate setpoints and to find compromises between comfort and economical demands. These concepts to integrate requirements concerning the preventive conservation of cultural heritage, where the velocity of changes in the controlled values has to be minimized, will be enhanced in the presented paper. In this paper two concepts to calculate fuzzy setpoints are proposed: the first one will be used for an offline calculation (section V-A) and the second one will be used to make an online adaption of setpoints (section V-B).

II. CLIMATE DEMANDS IN PREVENTIVE CONSERVATION

Methods in saving cultural heritage objects may be classified into restoration and conservation. Restoration methods are treatments of the object, with a manipulation of the material substance (maybe by exchanging or repairing). In contrast, conservation methods are characterized by operations, which do not interact directly with the material. Fundamentally, the use of conservation methods is preferred for saving the original state of the object. Especially methods of preventive conservation are coming up, where (among other things) the

environment of objects should be designed in a way that material ageing and damaging get slowed and delayed. The topic of analyzing the present climate, determining reasonable setpoints for the different climate values and optimization of climate control, is in focus of many research groups, as appeared to reports and proceedings like [8].

A. Stationary demands

Except for a few applications, the significant thermal climate value is the relative humidity ϕ and not the temperature ϑ . This can be explained by looking at chemical and biological damaging processes: they slow down, if the temperature is low. In defining a reasonable range for the relative humidity, such a simplified rule cannot be defined. Figure 2 shows different goals for relative humidity of different materials. It is obvious to use fuzzy theory to formulate setpoints of relative humidity as fuzzy number or fuzzy interval, to utilize the range of setpoints in management systems and to define compromises in applications with different demands.

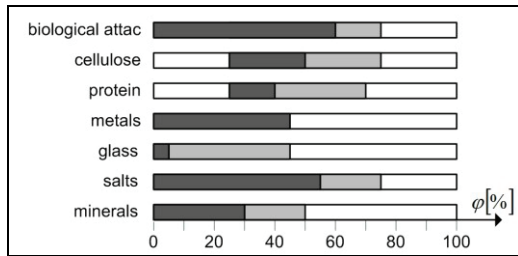


Figure 2. Stationary demands of relative humidity (modified from [9])

B. Dynamical demands

Furthermore, materials react on climate changes in their environment. In the stationary case, there is an equilibrium of environment and object climate (or the object state). If temperature in the environment changes, a heat flow at the material surface will start to reach another point of equilibrium, since the object's material serves as a heat storage. The same effect can be noticed on changes in humidity: the relation between the humidity in the air and the material states (like water content or inner stress) causes moisture flows. Based on the saturated vapor pressure of material and air, the relative humidity and not the absolute humidity should be focused. [10]

Hence, if there is a heat or moisture flow into or out of the material, the inner structure of the material has to transport energy or mass. This transport process fatigues the material, and if it is too fast, the inner structure will be damaged. But some materials are acclimatized during the transport process over the course of the years. They accustom their inner structure to historic climate cycles. [10]

C. Guidelines and standards

Some standards [11], [12] and guidelines [13] are published concerning the avoidance of such damaging processes. Also there are some quality climate classes published in [14]. Material-specific demands, the calculation of individual historical climates and the acceptable climate fluctuations in a time span can be found there. But it is not yet defined,

- how these fuzzy demands can be realized by an air conditioning system,
- how the setpoints can be calculated, if the historical climate (for all objects in a room!) is unknown,
- how to define a compromise between stationary and dynamical demands as well as to economical aspects and
- how to manage basic automation and planning setpoint trajectories in the case of an error.

III. DECISION MAKING IN FUZZY ENVIRONMENT

The task of decision making is to find the best solution for a value (or multiple values) inside a decision space. So we talk about an optimization problem. For the frequent case of several objectives, we even have a multi criteria optimization problem. Searching the best solution will be more difficult, if objectives are only inexactly, imprecisely or vaguely known.

A. Basic concept of fuzzy decision making

The theory of fuzzy decision making aims primarily at finding the best solution x^* from a set of alternatives x . Objectives are formulated as fuzzy sets. Objectives are classified in a set of n goals $\mu_{Gi}(x)$ (objectives to aim requirements, with $i=1, \dots, n$) and a set of m constraints $\mu_{Cj}(x)$ (objectives to avoid damages, with $j=1, \dots, m$). The question arises, how to aggregate all single objectives to an overall objective function for the elements of the decision space. Initially Bellman and Zadeh [15] suggest to create the intersection of all objectives and to determine the maximum of the resulting function as the best solution. Hence, we can aggregate all the goals to a new fuzzy set and all the constraints to a new fuzzy set. All goals and constraints may be combined to the set of decisions by creating the intersection [16]:

$$\mu_D(x) = \left(\bigcap_{i=1}^n \mu_{Gi}(x) \right) \cap \left(\bigcap_{j=1}^m \mu_{Cj}(x) \right) \quad (1)$$

The optimal decision x^* can be determined (shown in figure 1):

$$\mu_D(x^*) = \max \{ \mu_D(x) \} \quad (2)$$

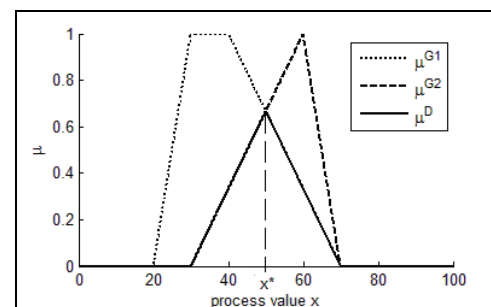


Figure 3. Fuzzy decision making of two fuzzy goals

Theoretical constraints can also be formulated as goals. For instance, if an objective is nominated to avoid a bad state, it will be possible to formulate this in a way that it will be good to reach the opposite. Hence, after reformulating the constraints it is sufficient to focus the goals [17]. Further information about fuzzy decision making can be found in [16], [18], [19] and [20]. Applying this theory in climate management, there are two major issues to be discussed: how to weight the goals and how to handle extremely contrasting demands.

B. Weighting objectives

In the concept described in section A, the importance of all goals in the intersection is equivalent. In some applications this is not correct, because single objectives have to be weighted. Bellman and Zadeh [16] suggest at first to weight single goals by using multiplicative factors. Instead of the aggregation using the intersection, the sum of all sets is advised:

$$\mu_D(x) = \sum_{i=1}^n a_i \cdot \mu_{Gi}(x) \quad (3)$$

To stay in the fuzzy world, it is necessary that the maximum of the decision set is not higher than one. For equation (3) this may be reached, if the sum of all weighting factors a_i is equal to one. As an alternative concept, exponents between zero and infinity may be used to weight single objectives. If the exponent is near infinity, the set will be equal to the kernel-function of the initial set (all elements round down to zero, except the elements with the degree of one), which means that the objective is very high weighted. In the opposite case, if the exponent is near zero, the set will be equal to the support (all elements will be round to one, except the elements with the degree of zero), which means that the objective is not very important. So, the intersection may be used for aggregation:

$$\mu_D(x) = \bigcap_{i=1}^n \mu_{Gi}(x)^{a_i} \quad (4)$$

This concept is also known in the area of fuzzy modifiers, where these powering operations are used as methods to describe the fuzziness in a linguistic term and to consider linguistic hedges in modeling of knowledge based systems [21], [22]. That is pretty much the same as weighting of objectives. A drawback of this concept is that the weighting process is not very obviously, because there are different ranges for dilatation (between zero and one) and concentration (between one and infinity). As an extension of this concept, we suggest to introduce an additional value λ_i by using the following mark:

$$\mu_{Gi}^{(\lambda_i)}(x) = \mu_{Gi}(x)^{a_i} \quad (5)$$

The parameter is scaled from -1 to 1 and defined as:

$$a_i = \begin{cases} \frac{1}{1-\lambda_i} & \text{for } 0 \leq \lambda_i < 1 \\ 1+\lambda_i & \text{for } -1 < \lambda_i < 0 \end{cases} \quad (6)$$

Figure 4 shows the effect of the modification using equation (6). If the weighting value λ_i moves toward -1 , the shape will be deformed equal to the support-function and if the λ tends to 1 , the shape will be deformed to the kernel-function.

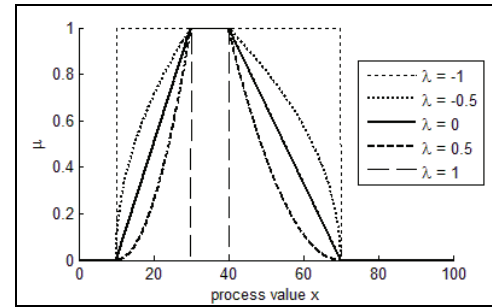


Figure 4. Effect of the weighting parameter λ_i to the membership function

C. Extremely contrasting demands

In some applications it can happen that a creation of an intersection is impossible. There will be no element in the set of alternatives where all membership functions are different to zero at once and finally an empty decision is resulting. This case occurs, if the demands are in an extreme contrast. In fuzzy decision making also values outside the appropriate area must be evaluated and it has to come to a decision about the reaction in such cases. It is necessary to distinguish those states, because a value far away from the kernel should not get the same bad rating as a value more close to it. This is why we should talk about an "inappropriate" and not about a "forbidden" area. The task before was to find the solution which satisfies all objectives equally; now the task is to find the solution where all objectives are unfulfilled in the same way.

To handle such scenarios, membership functions with degrees always higher than zero should be used. That can be done if suitable parametric membership functions (like the difference between two sigmoidal functions) are used or existing membership functions are manipulated. Remember: goals and constraints have finally been defined by human, where complicated functions may not be obviously parameterizable.

We prefer to keep the clearness of trapezoidal linear functions, because it is simple to define areas like "inappropriate" (outside the support), "appropriate" (inside the support) and "ideal" (inside the kernel), as shown in figure 1. In the classical trapezoidal function

$$\mu(x) = f_{Trap}(a, b, c, d) \quad (7)$$

the shape is defined by four parameters: a linear function increase from zero at a till one at b ; another linear function

decrease from one at c till zero at d ; between b and c all degrees are equal to one; all other degrees are zero. After defining this, we mitigate the crossing between the acceptable and the inappropriate zone to solve special cases as described in section A and we extend the conventional function by an additional parameter ε :

$$\mu(x) = f_{Trap\varepsilon}(a, b, c, d, \varepsilon) \quad (8)$$

The shape is defined as:

$$\mu(x) = \begin{cases} \varepsilon \cdot e^{\left(\frac{x-a}{\varepsilon(b-a)} - 1\right)} & \text{for } x \leq a + \varepsilon \cdot (b-a) \\ \frac{x-a}{c-a} & \text{for } a + \varepsilon \cdot (b-a) < x < b \\ 1 & \text{for } b \leq x \leq c \\ \frac{d-x}{d-c} & \text{for } c < x < d - \varepsilon \cdot (d-c) \\ \varepsilon \cdot e^{\left(\frac{d-x}{\varepsilon(d-c)} - 1\right)} & \text{for } x \geq d - \varepsilon \cdot (d-c) \end{cases} \quad (9)$$

The effect of choosing ε is shown in figure 5. We justify our approach as follows: if we look at a fuzzy objective it is possible that an ideal area (with equivalent ratings inside) could be defined by an expert; but the boundaries could not be defined clearly.

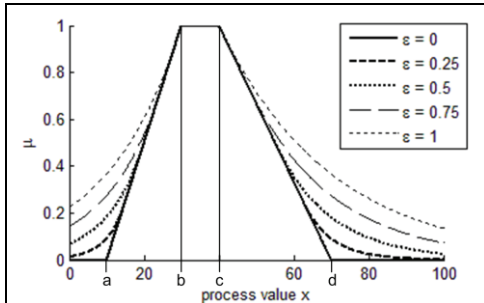


Figure 5. Effect of breaking the hard constraint

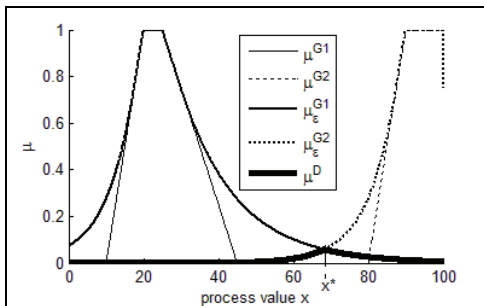


Figure 6. Decision making with controversy goals

Using this concept, it will always be possible to find a solution, also for controversial demands. An example is shown in figure 6: Two fuzzy sets defined according to equation (9) are intersected according to equation (1). The optimal process value x^* is obtained from equation (2).

D. Manage the trajectory of setpoints

The requirements of a controlled variable can usually be characterized by different criteria. First of all, stationary goals μ_{GS} should be reached to work in desired operating points. Generally, the necessary operations to reach the stationary goals should be done very efficient with low costs, thus aspects of economy μ_E are added. Finally, dynamical demands μ_{GD} have to be considered; these goals are dependent on past values of the controlled variable (as an example figure 7 shows a decision making process):

$$\mu_{GD}(x, x(k-1)) = f_{Trap\varepsilon}(x(k-1) + [a, b, c, d], \varepsilon) \quad (10)$$

All goals may be aggregated to the decision set:

$$\mu_D(x) = \mu_{GS}(x) \cap \mu_E(x) \cap \mu_{GD}(x, x(k-1)) \quad (11)$$

Hence, the question arises, how to weight the interacting of goals. It is obvious that all requirements are coupled: a higher performance may be reached by a high weighted stationary goal on the one hand and by a low weighted dynamical goal on the other. Surely, both cases will involve increasing costs. Based on the normalization, one goal may be inflexible and the other two goals may be mutually weighted.

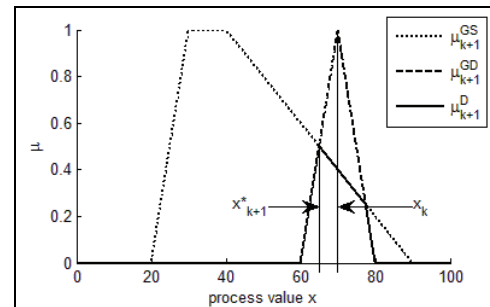


Figure 7. Decision making of stationary and dynamical demands

IV. THE AIR CONDITIONING PROCESS

Every climate value (thermal or non-thermal) can be described by a mass or energy balance. By summarizing all flows into the room, we get an universal balance equation for the indoor value σ^R , where the exchange of air with the outdoor climate is named as σ^E , buffering and storage effects are described by σ^S , transmission effects by σ^T , disturbance and non-manipulable inner loads by σ^Z and at last the manipulable inner sources named as σ^Y are added:

$$\dot{\sigma}^R(t) = \dot{\sigma}^Z(t) = \dot{\sigma}^E(t) + \dot{\sigma}^S(t) + \dot{\sigma}^T(t) + \dot{\sigma}^Z(t) + \dot{\sigma}^Y(t) \quad (12)$$

A. Calculation of temperature and humidity

Taking the focus on temperature values, it is necessary to integrate the heat flows with a capacity (product of density ρ , specific capacity of air c and the room volume V_R of); using equation (12) and setting the universal value σ to the heat quantity Q :

$$g^R(t) = \frac{1}{\rho \cdot c \cdot V_R} \cdot \int \dot{Q}^{\Sigma}(t) \cdot dt \quad (13)$$

Model structures and control concepts of the temperature are well known and can be found in the corresponding literature [1], [23]. Taking the focus on the humidity, it is necessary to integrate the flows of (absolute!) humidity with a capacity (as the volume) of the room; using equation (12) and setting the universal value σ to the moisture content f :

$$f^R(t) = \frac{1}{V_R} \cdot \int \dot{f}^\Sigma(t) \cdot dt \quad (14)$$

As already mentioned above, the most important physical value of air conditioning is not the absolute humidity but rather the relative humidity, which is a temperature-dependent function and may be calculated by equation (15), where R^S is the specific gas constant and p^S is the saturated vapor pressure, which can be calculated by using appropriate functions (look at [24]). A structure of the process is shown in figure 8.

$$\varphi^R(t) = \frac{f^R(t) \cdot R^S \cdot g^R(t)}{p^S} \quad (15)$$

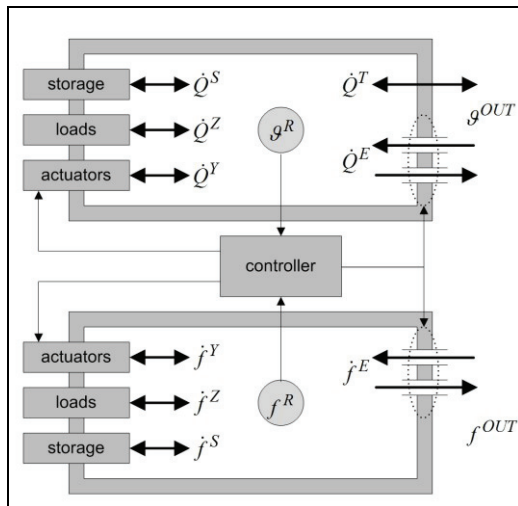


Figure 8. Control schema and influences on the indoor climate

B. Manipulating and controlling the process

It is obvious that the task of control thermal values is coupled to temperature and humidity, especially the temperature dependence of relative humidity and the influence

of the ventilation rate. Additional to the manipulation of the ventilation rate, heating and cooling may be used to control the temperature. Humidifier and dehumidifier may be used to control the moisture balance. There are special requirements in the area of preventive conservation, because installations of air conditioning systems needs often a huge installation space and are also very expensive. Furthermore, it is also not allowed to damage the substance of historical buildings by additional installations. Finally, there are only a few options left to manipulate the process. Tasks of air conditioning may be divided into tasks of different time scales:

- short-term: measure process states, control of the variables in order to meet the given setpoints, aggregation of process information, time span: minutes till hours (daily fluctuations)
- medium-term: online optimization of setpoints, planning trajectories, time span: days (weather fluctuations)
- long-term: seasonal optimization, time span: weeks till month (seasonal fluctuation)

Short-term tasks are usually handled in concepts of basic automation, where standard controllers are used or manual operations (on/off switching of actuators, manual aerating) are provided to the process. Medium-term and long-term tasks can be aggregated to tasks of the process management system (PMS), which calculates the setpoints for the different control variables online (so far as online process information is available). Figure 9 shows the division of tasks and decision making in different levels of the automation structure.

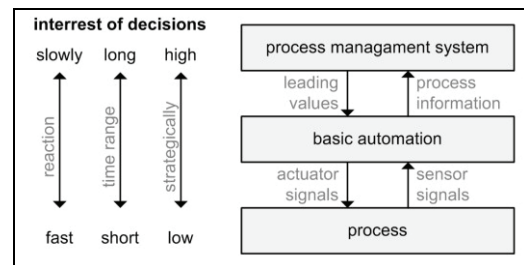


Figure 9. Levels of process automation

V. APPLICATION: CALCULATION OF CLIMATE SETPOINTS

This section describes a concept to find the optimal setpoints for the climate in applications of preventive conservation. Initially, applications where elements of basic automation are already present are considered. But this will also be a task, if the process is controlled by manual operations and the process staff is trying to reach the setpoints in that way. In this case, the PMS works as a decision support system.

A. Offline planning of fuzzy trajectories

The first approach for using fuzzy decision making is the design of a planning system. In interaction with the user, a local climate profile and stationary demands of people and cultural heritage have to be defined (maybe by using an additional configuration system). In this case there is no information about the process state, hence the system is only a

stationary offline system, dynamical aspects cannot be taken into account. Taking a priori information of the local climate in the course of the year into account, only the seasonal component is estimable, as effects of weathers and daily fluctuations are unknown.

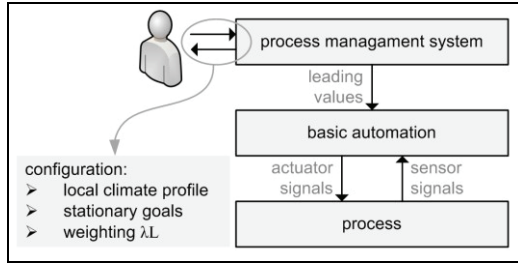


Figure 10. Structure of the planning tool

The outdoor climate of temperature and humidity can be approximated using a sine function [24]; hence, an appraisal of the economical demand to control a specific value is calculable. As an example, we plan the fuzzy setpoints of relative humidity in a room, where the indoor climate is controlled by components of the basic automation. Ignoring short-term effects, the demand of humidifying and dehumidifying may be calculated by looking at the required power in order to compensate the losses of absolute humidity by the mean of the natural air exchange $\dot{V}^E$:

$$\dot{f}^Y(t) \approx -\frac{1}{V} \cdot [f^{OUT}(t) - f^R(t)] \cdot \bar{V}^E \quad (16)$$

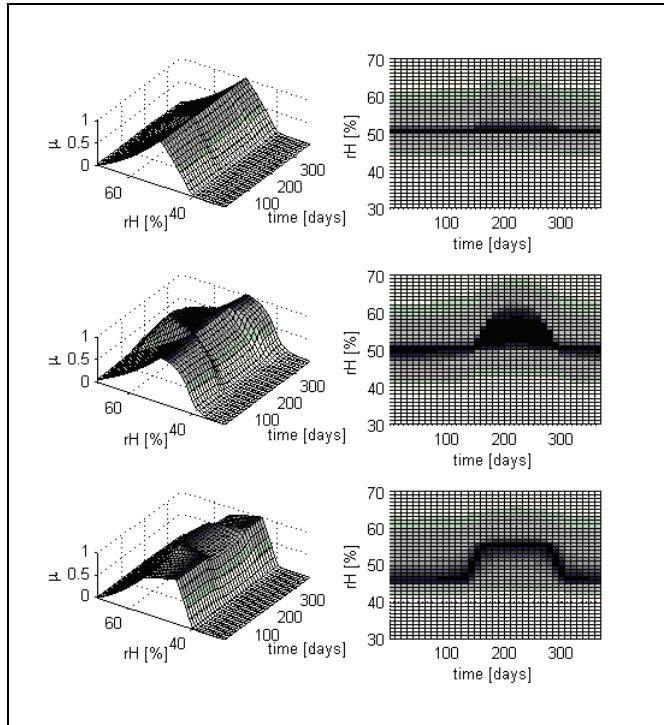


Figure 11. Fuzzy setpoints for relative humidity in the course of the year at different configurations. Left: stationary goal $f_{Trape}(40, 50, 50, 70, 0.1)$ and $\lambda_L = 0$. Middle: stationary goal $f_{Trape}(40, 50, 50, 70, 0.1)$ and $\lambda_L = -0.5$. Right: stationary goal $f_{Trape}(40, 45, 55, 70, 0.1)$ and $\lambda_L = 0$.

Using equation (15), the economical demand may be calculated for various setpoints of relative humidity at every time step:

$$\dot{f}^Y(t) \approx -\frac{1}{V} \cdot \left[\frac{\varphi^{OUT}(t)}{g^{OUT}(t)} - \frac{\bar{\varphi}^R(t)}{g^R(t)} \right] \cdot \frac{p^S}{R^S} \cdot \bar{V}^E \quad (17)$$

We use the following relation to create a fuzzy membership function of the cost objective applying the result of (17):

$$\mu_{EL}(\varphi^R, t) = 1 - \frac{|\dot{f}^Y(t)|}{\max |\dot{f}^Y(t)|} \quad (18)$$

To reduce the complexity of configuration, we define λ_L as a weighting parameter, hence we can calculate the trajectory of fuzzy setpoints over the year. Figure 11 shows some examples for different configurations:

$$\mu_{\phi L}(\varphi^R, t) = \mu_{GS}^{\langle \lambda_L \rangle}(\varphi^R) \cap \mu_{EL}^{\langle -\lambda_L \rangle}(\varphi^R, t) \quad (19)$$

B. Online process management system

Another approach for using the presented concept is an online PMS. In interaction with the user stationary and dynamical demands of people and cultural heritage have to be defined (may be using an additional configuration system again); but now there is no need of defining an outdoor climate profile (because of online measurements).

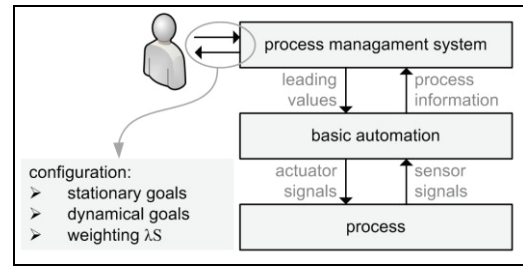


Figure 12. Structure of the process management system

Economical demands are calculated using online information of indoor and outdoor climate. We use equations like (17) and (18), but not over the course of the year (only for the present time). Furthermore, it is possible to calculate the membership function for dynamical goals, also using process information about the actual states. To reduce the configuration complexity, we do not weight the stationary demand (see above) and introduce a parameter λ_S as a weighting parameter between economical and dynamical demands, which may be justified obliviously.

$$\mu_{\phi S}(x, t) = \mu_{GS}(x) \cap \mu_{GD}^{\langle \lambda_S \rangle}(x, x(k-1)) \cap \mu_{ES}^{\langle -\lambda_S \rangle}(x, k) \quad (20)$$

VI. CASE-STUDY: SIMULATIONS OF A THE PMS

Based on simulations, in which a PMS has to generate optimal setpoints for an underlying control circuit of relative humidity, we will show the effectiveness of the proposed concept. This circuit in the basic automation level is using a feedback controller (PID) combined with a disturbance feed forward control (DFF). The structure is shown in figure 13.

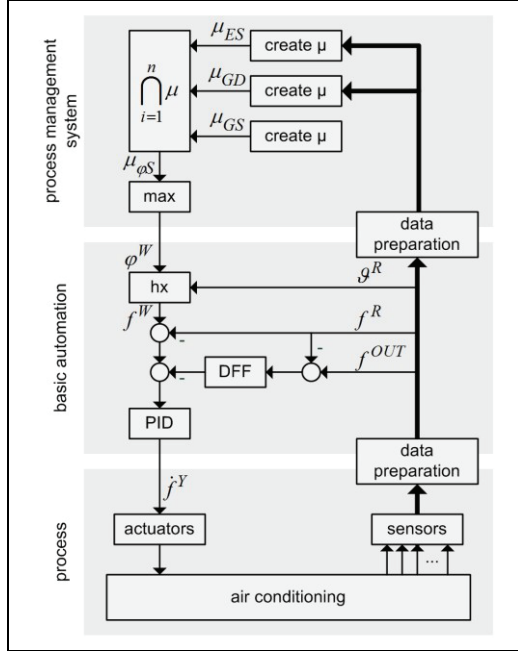


Figure 13. Structure of the controller in the case study

The PMS works dependent on the process values in medium-term range, a discrete filter (moving average of 24 hourly samples) is used to blind out short-term effects, which must be handled by basic automation. The setpoint of relative humidity gets an update every hour. Equation (20) is used for calculating the decision set. Thus the design parameter is λ_S . For the simulation we use a simulation environment of a building model in MATLAB/Simulink, which depends on first order balance equations of energy as well as additional components like storage effects for heat and moisture of the room. For details regarding to building physics and simulation look at the respective literature [25], [26] and [1].

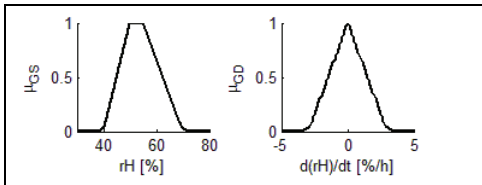


Figure 14. Stationary and dynamical goals in the case study

The goals are fuzzy values, the stationary demand is defined as appropriate in the area from 30% to 55% and in the vicinity of 35% and 50% the value is ideal. Regarding dynamical aspects, no changes would be the best solution; changes about $\pm 3\%$ per hour are accepted. To create a fuzzy membership function, we use equation (9) with a value ε of 0.1 for all membership functions. A scenario of outdoor climate

and initial conditions is defined and simulated at different configurations of λ_S (figure 15). It is obvious that the design parameter λ_S has a significant influence on the dynamic behavior of the controlled variable. In a more detailed analysis of the simulation results, the membership of all simulation data to the stationary and the dynamical goal is determined just as the power (needed for humidification) is cumulated. The normalized and scaled values are plotted in figure 16.

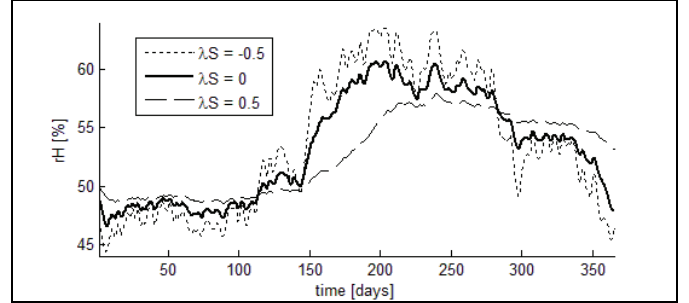


Figure 15. Simulation results: behaviour of the controlled relative humidity at various weightings.

As expected, choosing a higher λ_S (higher weighting of the prevention of high gradients) leads to lower economical effects. Considerable is the correlation of the effect of choosing λ_S to stationary and dynamical demands, which is caused at the coevally opposed weighting of economical aspects.

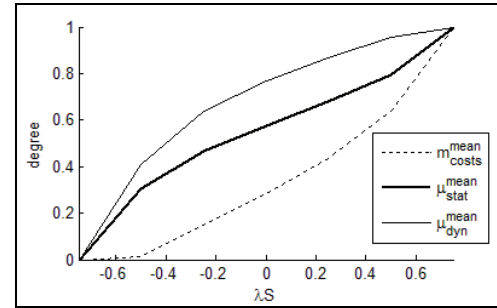


Figure 16. Simulation results (normalized and scaled): sum of power demands and means of bad ratings

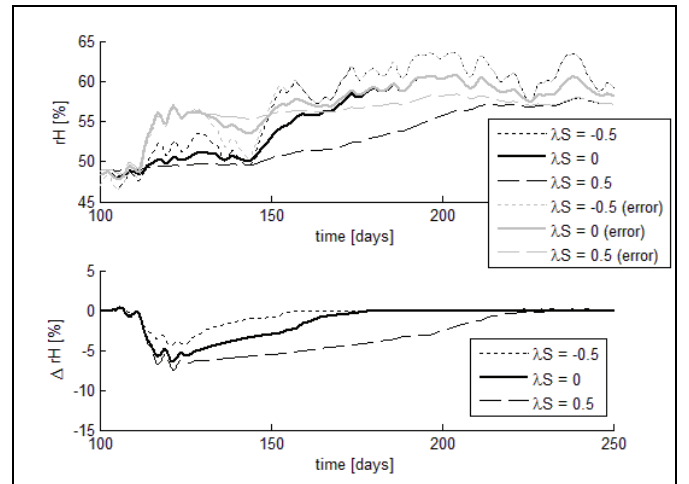


Figure 17. Dynamical behaviour of the controlled variable after an error (between the 105th and the 130th day): simulation results (above) and difference to normal behaviour (below)

Analyzing the second effect of using the PMS, an error in the technical equipment is simulated. The task of the PMS is now to guarantee the return of the process back to the optimal sequence of setpoints (depicted in figure 17). After reactivation of the equipment, the parameter λ_s defines the velocity to reach the behavior in the normal operation; the activation is also bumpless. Hence, the PMS also resumes the task of planning trajectories.

VII. CONCLUSION AND OUTLOOK

The theory of fuzzy decision making can be used to make decisions in applications where the demands of the controlled process are only inexact, imprecise or vague known. We presented established weighting methods and suggested a simple principle for using the powering operator obviously. Furthermore, we discussed the problems of decision making in the case of controversial demands and suggested a principle to transform hard constraints in trapezoidal membership functions.

Applications of air conditioning, especially in the area of preventive conservation are complex tasks, where the demands to avoid climate damages are only roughly known. There are some goals defined in norms, but no method how to find a compromise between the different demands, for instance how to weight stationary and dynamical demands. The presented approach and the simulations of a process management system were presented in this paper. Especially for the use in preventive conservation such a system may be used to find compromises between stationary and dynamical goals as well as to economical aspects.

In following work, we will use the concept of the process management system to generate future fuzzy setpoints and to optimize future manipulating operations in cooperation with the theory of multistage fuzzy control [26], maybe for planning an optimal ventilation sequence. Furthermore, we will expand the theory for MIMO processes, especially to combine the generation of setpoints for relative humidity and temperature.

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