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Gradient auto-tuned Takagi–Sugeno Fuzzy Forward control of a HVAC system using predicted mean vote index

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ABSTRACT

Controllers of HVAC systems are expected to be able to manipulate the inherent nonlinear characteristics of these large scale systems that also have pure lag times, big thermal inertia, uncertain disturbance factors and constraints. In addition, indoor thermal comfort is affected by both temperature and humidity, which are coupled properties. To control these coupled characteristics and tackle nonlinearities effectively, this paper proposes an online tuned Takagi–Sugeno Fuzzy Forward (TSFF) control strategy. The TS model is first trained offline using Gauss–Newton Method for Nonlinear Regression (GNMNR) algorithm with data collected from both building and HVAC system equipments. The model is then tuned online using the gradient algorithm to enhance the stability of the overall system and reject disturbances and uncertainty effects. As control objective, predicted mean vote (PMV) is adopted to avoid temperature–humidity coupling, thermal sensitivity and to save energy at the same time. The proposed TSFF control method is tested in simulation taking into account practical variations such as thermal parameters of buildings, weather conditions and other indoor residential loads. For comparison purposes, normal Takagi–Sugeno fuzzy and hybrid PID Cascade control schemes were also tested. The results demonstrated superior performance, adaptation and robustness of the proposed TSFF control strategy.

1. Introduction

The increase in energy consumption and demand in the last few decades encourages the investigation of new methods to reduce energy losses. The HVAC systems contribute a significant share of energy consumed in buildings. So it is advisable to find methods to reduce the rise of energy consumption in HVAC systems. But energy and indoor thermal comfort in buildings hold a contradiction; control devices are expected to balance between energy saving and achieving occupant satisfaction at the same time [1,2].

For controlling these devices, PID controllers are widely used because of their simple structure and their relative effectiveness, which can be easily understood and executed by practical implementations [3]. However, PID controllers are reliable only if the parameters of the system under consideration do not vary that much. On the other hand, variations in the operating condition of the HVAC system will cause change in the parameters of the system. These variations can be due to many factors such as water's chilled temperature, weather and occupancy level, which change from day to night. In short, the system is time variable and highly nonlinear. For these reasons, even for a single HVAC system, the use of a constant set of PID parameters will not give best results [4,5]. To obtain good PID control performance, the PID parameters should be tuned continuously, which is time-consuming and dependent on the experience of the one who adjusts them.

Furthermore, despite the non-stopping continuous research on improving PID algorithms, requirements for high product quality, subsystem unification and energy integration have resulted in nonlinearity and pure lag time for most of modern HVAC systems. These main characteristics have rendered many PID tuning techniques insufficient for dealing with these modern HVAC systems, which are categorized as Multi-Input Multi-Output (MIMO) processes [6,7]. Furthermore, the tuning of PID parameters in MIMO plants is difficult to obtain because tuning the parameters of one loop affects the performance of other loops, occasionally destabilizing the entire system. Therefore, most studies in the field of the HVAC system control tends to belong to artificial intelligence; neural network (NN) [8,9], fuzzy control [10,11], adaptive fuzzy neural network [12–14], etc.

Fuzzy logic control is used in HVAC systems for its capability in dealing with non-linearity as well as its capability to handle MIMO plants. Moreover, in most cases, fuzzy logic controllers are used because they are characterized by their flexibility and intuitive use [15]. Two types of fuzzy inference system (FIS) models, Mamdani

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FIS and Sugeno FIS, are widely used in various applications [16]. The differences between these two FIS models befall in the consequents of their fuzzy rules; and differing in their aggregation and defuzzification procedures. Researchers found that Sugeno FIS runs faster, is more dynamic to input changes and is more economical in the number of input fuzzy sets compared to Mamdnai FIS. It is also observed that Sugeno FIS is more accurate since the results that were generated were closer to what was expected [17–19]. Jassbi et al. [20] concluded that Sugeno FIS performs better than Mamdani FIS with respect to noisy input data. Furthermore, Sugeno FIS is more responsive and that is due to the fact that when the noise becomes too high (i.e. when the input data has drastically changed), Sugeno FIS reacts more strongly and its response is more realistic. In recent years, the learning methods based on using fuzzy control emerged as a vital tool in application to control nonlinear systems, including HVAC systems. For large scale HVAC systems, iteration tuning makes better a control system and gets minimum cost on a system level [21].

A Takagi–Sugeno Fuzzy Forward (TSFF) controller is a forward type controller. The main benefits of implementing such controllers are to speed up system response and reduce any overshot [22]. These controllers can be made more robust by auto-tuning them online to deal with any change of plant parameters, disturbances and heating/cooling loads. The speed of TSFF tuning is higher than the conventional backpropagation type neural network [23].

Temperature and relative humidity are correlated variables, so to control them at specific values is a complex task. One of the proposed solutions is the addition of a reheating coil to overcome this coupling relation. However, this increases the power consumed to control the conditioning space. A better solution would be the use of predicted mean vote (PMV) as a reference for the HVAC system, which will result in several features and advantages; first of all, it means that the thermal sensation of the conditioned space is controlled directly compared to previous methods, such as the widely used indoor temperature variable as reference signal method, where the thermal sensation is controlled inefficiently. Another direct advantage is the flexibility to control coupled variables like temperature and relative humidity without the need to decouple them. In this way, the controller can easily track the desired thermal sensation for the conditioned space by controlling more controllable variables like the indoor air velocity and the flow rate of the refresh air [24]. Moreover, these controlled variables can be fitted (optimized) by the controller according to the amount of impact on the reference output. Therefore, using the PMV index as the target set value for the indoor conditioned space is a better and more suitable choice than using temperature because the PMV changes dynamically so as to suit the constantly changing indoor environment, and this will be useful to HVAC control systems aimed at both controlling thermal comfort and saving energy [25].

There are numerous mathematical relationships to represent thermal comfort. Fanger [26] representation was accepted to be the closest one to the real behavior of the indoor actual model, and that is the reason why it is adopted in ASHRAE Standard 55-92 [27] and ISO-7730 [28]. In this study, the HVAc system and PMV models are integrated to evaluate indoor thermal comfort situations. The first model is an extensive and elaborate model of the building and air handling unite (AHU). It is designed to represent the real system by the consolidation of five subsystems (pre-cooling coil, mixing air chamber, main cooling coil, building structure and conditioned space) interacting with each other. The second model is a fuzzy PMV model which is regarded as a white-box model. Then a TSFF control system is designed. The construction of the TSFF is based on two types of learning; offline and online. The offline learning method is performed using the Gauss–Newton Method for Nonlinear Regression (GNMNR) algorithm which has the capability to express the knowledge acquired from input–output data in the form of layers of parameters. The online tuning of the TSFF is accomplished using the gradient method to modulate the parameters of layers obtained from the offline learning. Most of control research in HVAC systems use PID control as a benchmark to compare with their new controllers [29–38]. In our case, a conventional PID control method would exhibit disability to control the plant system due to the fact that the MIMO model used in this study is a large scale system model that has nonlinearity, pure lag time, big thermal inertia, uncertain disturbance factors, and constraints in valves and dampers. Therefore, this work considers a Takagi–Sugeno fuzzy controller with fixed parameters and a hybrid PID-cascade controller [29–33] as benchmarks.

In general, when comparing the performance of fuzzy logic and PID with anti wind-up control systems, the fuzzy algorithm achieves the imposed overshot and a settling time required specifications [39]. Furthermore, the performance of the traditional PID controller scheme is limited when applied to AHU processes due to the coupled temperature and humidity properties of the system, especially when significant load variations and disturbances occur [40]. Therefore, it is the aim of this study to investigate techniques to enhance the control performance of indoor thermal comfort in comparison to the conventional hybrid PID-cascade and the normal Takagi–Sugeno fuzzy controllers. Tests were conducted taking into account practical variations such as thermal parameters of buildings, weather conditions and other indoor residential loads; between the three different schemes (the proposed method and the two conventional methods) to demonstrate the efficiency of the proposed method.

2. Model

The frame work of this section is to describe the HVAC system and PMV sensor models, which are the plant on which indoor thermal sensation is to be controlled.

2.1. HVAC system model

The HVAC mode consists of enormous number of variables and parameters that make modeling a difficult task. To reduce the complexity of building the model, Homod et al. [41,42] divided the HVAC system into five parts; pre-cooling coil, mixing air chamber, main cooling coil, building structure (opaque surfaces structure, slab floor structure and transparent fenestration surface at the structure) and conditioned space. The consolidation of the five parts together is discussed in the previous paper [41] to provide the overall equation model as follows:

$$\begin{bmatrix} T_r(s) \\ \omega_r(s) \end{bmatrix} = \begin{bmatrix} T_{1,1}(s) & T_{1,2}(s) & T_{1,3}(s) & T_{1,4}(s) & T_{1,5}(s) & \cdots & T_{1,10}(s) & T_{1,11}(s) & T_{1,12}(s) \\ T_{2,1}(s) & T_{2,2}(s) & T_{2,3}(s) & T_{2,4}(s) & T_{2,5}(s) & \cdots & T_{2,10}(s) & T_{2,11}(s) & T_{2,12}(s) \end{bmatrix} \times \begin{bmatrix} \dot{m}_w(s) \\ \dot{m}_{mw}(s) \\ \dot{m}_{os}(s) \\ \dot{m}_r(s) \\ T_o(s) \\ \omega_o(s) \\ f_4 \\ \dot{Q}_{ig,l} \\ A_{slab} \\ f_{DR} \\ k_2 \\ T_r(s) \end{bmatrix} \quad (1)$$

where

$T_{1,1}(s) \quad T_{1,2}(s) \quad \cdots \quad T_{1,12}(s)$ and $T_{2,1}(s) \quad T_{2,2}(s) \quad \cdots \quad T_{2,12}(s)$ represent the input factors. For a detailed description of all