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Comparative Analysis of Thermal Unit Control Methods for Sustainable Housing Applications

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Abstract

This study aims to develop different control strategies for application to nonlinear model of a thermal unit and compare their performances as an advanced thermal control methods for HVAC applications of sustainable buildings. The mathematical description of thermal unit was obtained exploiting a data-driven and physically meaningful nonlinear continuous-time model, which represents a test-bed used in passive air conditioning for sustainable housing applications. The presented controller strategies use both inside temperature and air flow control in the thermal unit. The proposed control schemes were assessed with extensive simulations and Monte-Carlo analysis in the presence of modelling and measurement errors. The contribution of this work consists of providing an application example of the design and testing through simulations, of a data-driven thermal unit control. Furthermore, this study provides an insight into different control strategies in air conditioning systems and helps the practitioners and HVAC learners to design proper controller solutions.

Keywords - thermal unit; modelling and simulation for control; advanced control design; artificial intelligence; nonlinear control design

1. Introduction

The distribution of energy consumption in Europe households was as follows in 2015: 50% for air conditioning, 13% for water heating and 12% for lighting and electric appliances [1]. Air conditioning systems provide buildings with heating/cooling functions and thermal comfort parameters including relative humidity and temperature. Thermal Units (TUs) play an essential role for supplying treated air with specified temperature to the conditioned space in the buildings. Hence, it is fundamental to understand the system behaviour of TUs in order to decrease energy consumption and achieve thermal comfort in buildings [2].

The TU system is a typical nonlinear time-variable multivariable system with disturbances in the view of control [3]. Many control methods use traditional controllers like on-off controllers, Proportional, Integral and Differential (PID) or Proportional and Integral (PI) regulators [4]. These controllers are simple and low-cost, however, sometimes are not able to produce accurate results. Moreover, the TU system has bilinear terms like temperature and mass flow rate, hence, advanced controllers must be replaced for an improved thermal comfort and a lower energy consumption. To overcome the problems stated above, Artificial Intelligent (AI) based controllers, namely, Artificial Neural Network (ANN), Fuzzy Logic (FL), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Model Predictive Controllers (MPC) have been applied for trying to achieve more comfortable environments in buildings [5]. FL controllers are based on human knowledge of the system behaviour and require no mathematical modelling. In addition to FL controllers, some authors studied ANN controllers to maintain a better thermal comfort for heating purposes [3]. Although ANN controllers presents interesting features such as learning, adaptation, fault-tolerance and generalization, some researchers studied more efficient control techniques based on ANFIS tool [5] and MPC for temperature control of buildings [1]. Note finally that many studies proved thermal comfort and energy efficiency using AI control techniques, however the performance of the AI based-methods were not compared with extensive simulations in most of them. This paper aims to design different control techniques with application to a nonlinear TU model developed by Ref. [6]. Another objective of the paper is to highlight the potential application of the proposed control strategies to real air conditioning systems and help the practitioners and HVAC learners to design better controllers in their work. To this aim, the simulations and comparisons have been implemented in the Matlab and Simulink environments.

2. Thermal Unit Model

The TU is part of a larger test-bed system for testing and numerical modelling of phase change materials (PCM) used in the passive air

conditioning for sustainable housing applications. The speed and temperature of air passing around the tested PCM can be freely regulated to meet the demanded test environmental conditions, as shown in Fig. 1. The air is conditioned by means of the considered heating element which is in a down stream series connection with a cooling unit.



Fig. 1. The TU test-bed and schematic description of the TU

For the system identification purposes the following system inputs are considered: the measured inlet air temperature, denoted T_i [K], and the air velocity, denoted v [m/s]. The outlet air temperature, denoted T_o [K], is the system output. The data acquisition experimental set-up has been designed such that the supplied power, denoted q [W], to the heating element is constant with the average reading of $q= 830$ [W]. The measurements of v , T_i and T_o are taken from the centre of the cross sectional area of the supply duct.

The energy balance equations of the TU, the control volume of air surrounding the TU and the adjacent duct walls can be expressed as:

$$C_h (dT_h(t)/dt) = q(t) - (UA)_h [T_h(t) - T_o(t)] \quad (1)$$

$$0 = (UA)_h [T_h(t) - T_o(t)] - v(t) \rho_a A_a c_a [T_o(t) - T_i(t)] - (UA)_{int} [T_o(t) - T_w(t)] \quad (2)$$

$$C_w (dT_w(t)/dt) = (UA)_{int} [T_o(t) - T_w(t)] - (UA)_{ext} [T_w(t) - T_a(t)] \quad (3)$$

Here, C_h [J/K] is the thermal capacity of the heating element, C_w [J/K] thermal wall capacity (insulated plywood), c_a [J/kgK] is the air specific heat capacity, A_a [m²] denotes the cross sectional area of the duct, ρ_a [kg/m³] is the air density. The heat transfer coefficient is denoted by U [J/m²K] while the product of the heat transfer coefficient and the efficient surface area, A [m²], through which the heat is transmitted is denoted by $(UA)_h$ [J/K] (when referred to the TU) $(UA)_{int}$ [J/K] (inner duct wall) and $(UA)_{ext}$ [J/K] (outer duct wall). The mean temperature of the heating element and wall temperature are denoted, respectively, by $T_h(t)$ [K] and $T_w(t)$ [K]. In (2), it is assumed that the passing air has negligible thermal capacity, hence the

left hand side of the equation equals to zero. A standard thermocouple type K has been used to measure the air temperatures. The accuracy is around 1 °C for the whole measurement range. The airflow has been measured using a Hot Wire Thermo-anemometer with declared accuracy of 5%. For further detail of the TU model, please see Ref.[6].

3. Development of Control Logics for Thermal Unit

TU process, which is basically a MISO system, has several nonlinear components like temperature and air flow. The general description of the dynamic model of TU can be expressed by the nonlinear dynamic function P :

$$y = P(u, t) \quad (4)$$

Here, y is the process output, u are the inputs and t is the time. The control strategy applied to the TU should determine the control input such that the controlled process is able to track a given reference $r(t)$ [6].

The control input is represented by the air flow input temperature $u(t) = T_i$, and the measured output is $y(t) = T_o$. In building HVAC control systems, bilinear terms are the most dominant ones. (Temperature)X(mass flow rate) can be given as an example in HVAC systems. Therefore, mass flow rate is considered as a measured disturbance, d . The data contain the inlet temperature, the air flow and the outlet temperature were obtained from the experimental work. The measurement errors were added to the the temperature and air flow signals.

The PID controller has been commonly used in many HVAC system applications [4,5]. The PID controller produces promising results based on the computation of the error $e(t)$ between the desired and the measured values of the output, i.e. $e(t) = r(t) - y(t)$.

The continuous-time control law of the PID regulator is described by (5):

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (5)$$

where K_p , K_i , K_d are the PID proportional, integral and derivative gains, respectively. The control of the TU is therefore carried out by a PI regulator (5) as shown in Fig. 2.

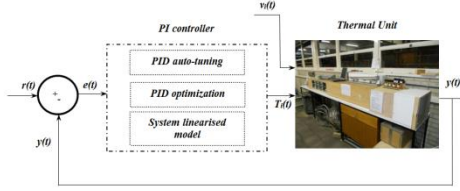


Fig.2. Block diagram of the TU system controlled by the PI regulator

In FL controller, controller actions are implemented in the form of if-then-else statements [7]. The controller design approach relies on the identification of transparent rule-based Takagi-Sugeno (TS) fuzzy models using an ANFIS tool implemented in the Simulink toolbox [8].

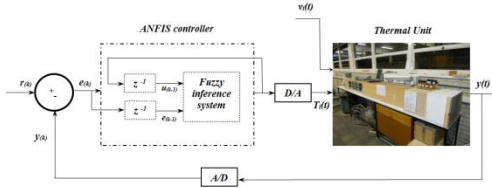


Fig.3. Block diagram of the TU system controlled by the ANFIS fuzzy regulator

The TS fuzzy model consists of a set of rules R_i , where the consequents are deterministic functions f_i :

$$R_i = \text{IF } x \text{ is } A_i \text{ THEN } y_i = f_i(x) \quad (6)$$

where $i = 1, 2, \dots, K$. Here, K is the number of clusters. The term x describes the antecedent variables, whilst y_i represents the consequent output. The fuzzy set A_i of the i^{th} rule is represented with a multivariable membership function in (7):

$$\mu_{A_i}(x) \rightarrow [0, 1] \quad (7)$$

Note finally that the final output y of the TS fuzzy model is represented as:

$$y = \frac{\sum_{i=1}^K \mu_{A_i}(x) y_i(x)}{\sum_{i=1}^K \mu_{A_i}(x)} \quad (8)$$

This paper also considers an effective approach called Fuzzy Modelling and Identification (FMID) toolbox developed in the Matlab environment. Fuzzy models are automatically generated from the measurements by a comprehensive methodology described e.g. in Ref. [9]. The system relies on the identification of rule-based fuzzy models and using the input-output data acquired from the controlled process. The method employs Gustafson-Kessel clustering method to divide the data into subsets with a common local linear behaviour. The identified fuzzy controller requires a proper model structure n and a number of clusters K . The developed method provides the parameters a_i , b_i and the estimation of the membership functions μA_i of the optimal controller minimising the tracking error $e(t)$ which is the difference between the reference signal $r(t)$ and the measured output $y(t)$.

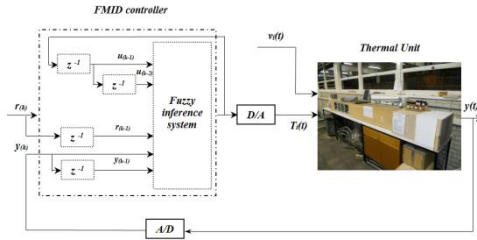


Fig.4. Block diagram of the TU system controlled by the FMID fuzzy regulator

The adaptive control method is based on the on-line identification of a second order discrete-time transfer function of an ARX time-varying model described in (9):

$$G(z) = \frac{b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \quad (9)$$

where z represents the unit advance operator and parameters are recursively estimated at each sampling time $t_k = kT$ where k is the number of samples and T is the sampling interval. The on-line identification employs Recursive Least Squares Method (RLSM) with adaptive directional forgetting.

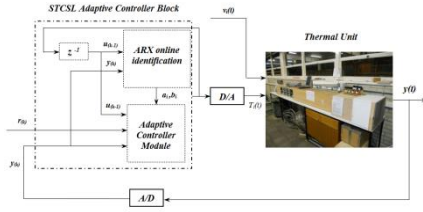


Fig.5. Block diagram of the TU system controlled by the adaptive regulator

Model Predictive Controller (MPC) predicts the future nonlinear system behaviours and generates a control vector over the prediction horizon. The controller implements current sampling time but optimises a finite time-horizon. The main advantage of MPC over PID controllers is predictive ability.

The MPC obtains control signals by minimizing objective function (J) as:

$$J = \sum_k^{k+Np} w [yk] (r_k - y_k)^2 + \sum_k^{k+Nc} w [uk] \Delta u_k^2 \quad (10)$$

where $w[yk]$ is the weighting coefficient reflecting the relative importance of the monitored output, $w[uk]$ is the weighting coefficient penalising relative big changes in u_k and $\Delta u_k = u_k - u_{k-1}$, Np represents the prediction horizon and Nc is the control horizon.

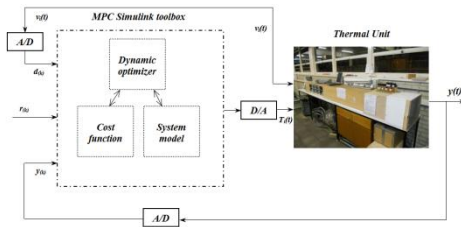


Fig.6. Block diagram of the TU system controlled by the MPC

The study recalls different control strategies including standard PI controller as well as AI techniques, such as FL, adaptive, model predictive controllers, which are used for the regulation of the outlet temperature of the TU system. The results of each regulator are compared in terms of Mean Sum of Squared Errors ($MSSE \%$), as shown in (11):

$$MSSE \% = 100 \sqrt{\frac{\sum_{k=1}^N (rk-yk)^2}{\sum_{k=1}^N (rk)^2}} \quad (11)$$

4. Simulation Results and Discussion

Most of the HVAC systems use classical PID regulators , the control of the TU is therefore carried out by a PI regulator as shown in Fig. 2.

The optimal proportional and integral gains are determined using the automatic PID tuning procedure and settled to $K_p=2$ and $K_i=3$, respectively. The PI controller has a settling time (T_s) of 2.17, with an overshoot ($S\%$) of 36.14. These values are computed by applying a step change in the reference output temperature from 39 °C to 40 °C. The tracking error ,achieved by using (5), is $MSSE\%= 1.65$ (Fig.7).

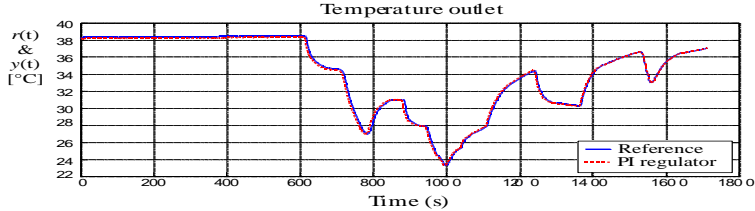


Fig.7. Outlet temperature controlled by the PI regulator

Classical controllers, such the PI controller used for the TU system, are robust and allow accurate tuning, hence have the benefit of quite straight-forward implementation. Nevertheless, the control laws are not efficient and can lead possible high maintenance costs. Therefore, the authors of this paper appraise advanced controllers in order to reduce energy consumption while maintaining the thermal comfort. To this aim, the PI regulator of TU system represents the reference controller for the generation of the data used by the advanced controller set-up. Fuzzy identification method is used to derive the models of the controllers by exploiting the so-called model reference control approach as described in Ref. [10]. The TS fuzzy controller , as described in previous section, is derived with the ANFIS tool, a sampling interval (T) of 0.1 s is exploited . Fig. 3 depicts the fuzzy regulator, which has a number of $K=3$ of Gaussian membership functions, with a number of delayed inputs and output $n=1$. The antecedent vector of the ANFIS controller is $x= [e_k, e_{k-1}, u_{k-1}]$. Table 1 highlights the achieved performance of the regulator obtained with the ANFIS tool. In this case, the settling time is $T_s = 2.21$, with an overshoot of $S\%=38.22$ and a $MSSE\%= 1.07$ (Fig.8).

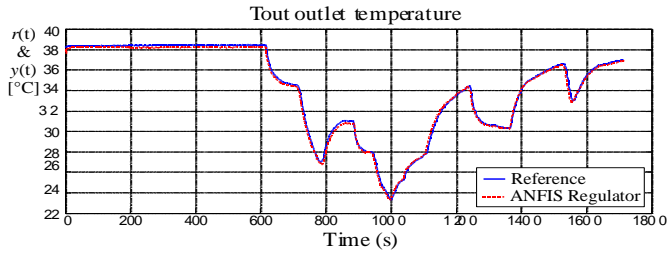


Fig.8. Outlet temperature controlled by the ANFIS regulator

In this work, a second fuzzy regulator was implemented by using the same data from the standard PI controller of the TU system. The regulator uses the FMID tool which predicts the optimal shapes of the membership functions of μ_A . Fig. 4 shows the implementation of the fuzzy regulator with a number of clusters $K=3$, number of delays $n=2$ and the antecedent vector of $x = [u_{k-1}, u_{k-2}, r_k, r_{k-1}, y_k, y_{k-1}]$. The reference signal is tracked with a $MSSE\%$ of 1.14. In this case, the settling time is $T_s = 3.98$ s with a maximum overshoot $S\%$ of 41.65 (Fig.9).

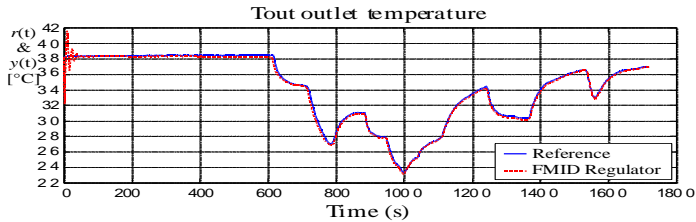


Fig.9. Outlet temperature controlled by the FMID regulator

On the other hand, an adaptive controller was developed by using the online procedure recalled in previous section. Fig.5 shows the block diagram of the adaptive controller used for TU system. Time-varying parameters have been settled to $\delta = \omega = 1$ which are defined as damping factor and natural frequency, respectively. The settling time of the adaptive controller is $T_s = 3.65$ s with a maximum overshoot $S\%$ of 40.18 and the tracking error of $MSSE\% = 1.18$ (Fig.10).

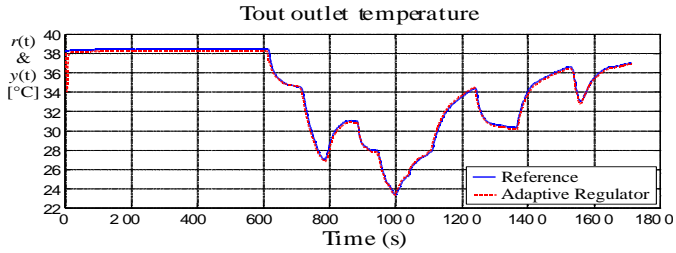


Fig.10. Outlet temperature controlled by the adaptive regulator

With reference to the MPC strategy recalled in previous section, the MPC were developed for the TU system (Fig.6). Note that the MPC of the TU uses a prediction horizon of $N_p=10$ and a control horizon of $N_c=2$. The weighting parameters were selected as $w_{yk}=0.1$ and $w_{uk}=1$ in order to reduce abrupt changes of the control input that would increase the energy consumption. In this case, the settling time is $T_s=1.85s$ and the overshoot is $S\%=35.51$ with a tracking error of $MSSE\%=0.41$ (Fig.11).

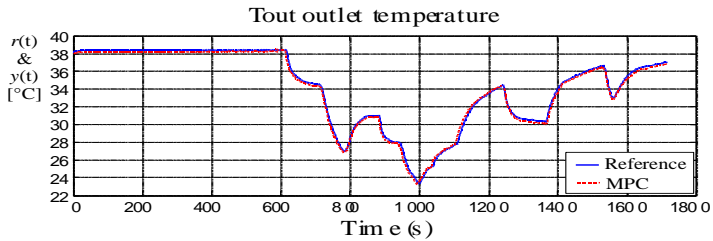


Fig.11. Outlet temperature controlled by the MPC

Table 1 depicts the comparison of the results achieved from different regulators used for the TU system in terms of settling time (T_s), overshoot ($S\%$) and tracking error ($MSSE\%$).

Table 1. Comparison of the proposed controller performance in terms of MMSE, Settling Time and Overshoot

Controller Type	Settling time (T_s)	Overshoot ($S\%$)	MMSE% (Nominal value)
PI	2.17	36.14%	1.65 %
ANFIS	2.21	38.22%	1.07%
FMID	3.98	41.65%	1.14%
Adaptive	3.65	40.18%	1.18%
MPC	1.85	35.51%	0.41 %

The MPC implementation is able to track the reference signal very accurately, thus maintaining the thermal comfort for energy-efficient buildings. In addition, ANFIS controller has good values of settling time, overshoot and the tracking error compared to the other ones. The PI regulator leads to the second best settling time as it uses auto-tuning in the Simulink environment in order to optimise parameters.

5. Robustness evaluation

This section presents further simulation results and the robustness features of the proposed controllers with respect to parameter variations. The robustness evaluation was performed according the approach already described in detail in Ref. [11]. The Monte–Carlo (MC) tool is useful as the control strategy performances depend on the error magnitude due to the model approximation and uncertainty, as well as on input–output measurement errors. The MC analysis describes TU model parameters as Gaussian variables with standard deviations of 20% corresponding to the maximal error values. Therefore, for performance evaluation of the control schemes, the best, average, and worst values of the *MSSE%* performance index were computed, and experimentally evaluated with 500 Monte–Carlo runs, as shown in Table 2.

Table 2. Comparison of the performances in terms of MSSE%

Controller Type	MSSE% Best case	MSSE % Worst case	MSSE% average value
PI	1.44%	3.14%	1.65 %
ANFIS	1.03%	2.33%	1.07%
FMID	1.10%	2.47%	1.14%
Adaptive	1.06%	1.78%	1.18%
MPC	0.38%	0.81%	0.41 %

Note finally that, MC analysis is an effective tool in presence of uncertainty and modelling errors and can be used for testing the suggested control methods for TU system.

6. Conclusion

In this paper, different control schemes varying from PI regulator to MPC were implemented to a nonlinear TU model, which represents a part of a larger system used for PCM in passive air conditioning for sustainable housing applications and the results were compared with the measurements. The feasibility and robustness issues of the proposed tools were demonstrated experimentally. The proposed control schemes were assessed with extensive simulations and Monte-Carlo analysis in the presence of modelling and measurement errors. Some final comments can be drawn

here. The achieved results showed that AI-based controllers can be successfully used for the regulation of the temperature of TU systems. Compared to the classical control approach, the TU model can be well described by advanced control techniques. MPC presented the best values of settling time, maximum overshoot and tracking error. However, the MPC strategy requires extra effort to find a suitable construction. The fuzzy-based controllers were based on the learning accumulated from off-line simulations but it is time-consuming to train the model properly. MC simulation tool was effective to facilitate the validation of the considered control schemes for application to real HVAC systems.

In this paper, the temperature of air and the air flow were taken into account; future works will focus on trying to extend the developed controllers to control more thermal comfort parameters, such as relative humidity, air flow and temperature. Moreover, the real evaluation of the MC analysis will be presented.

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