Building and Environment 72 (2014) 287–299

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Coupling a neural network temperature predictor and a fuzzy logic controller to perform thermal comfort regulation in an office building

Antonino Marvuglia [a], Antonio Messineo [b,*], Giuseppina Nicolosi [b]

[a] Public Research Centre Henri Tudor (CRPHT), Resource Centre for Environmental Technologies (CRTE), 6A, Avenue des Hauts-Fourneaux, L-4362 Esch-sur-Alzette, Luxembourg

[b] Faculty of Engineering and Architecture, University of Enna "Kore", Cittadella Universitaria, 94100 Enna, Italy

ARTICLE INFO

Article history:
Received 21 May 2013
Received in revised form
2 October 2013
Accepted 30 October 2013

Keywords:
Indoor thermal comfort
Artificial neural networks
NNARX
Fuzzy logic
Controller
Temperature forecast

ABSTRACT

The paper describes the application of a combined neuro-fuzzy model for indoor temperature dynamic and automatic regulation. The neural module of the model, an auto-regressive neural network with external inputs (NNARX), produces indoor temperature forecasts that are used to feed a fuzzy logic control unit that simulates switching the heating, ventilation and air conditioning (HVAC) system on and off and regulating the inlet air speed. To generate an indoor temperature forecast, the NNARX module uses weather parameters (e.g., outdoor temperature, air relative humidity and wind speed) and the indoor temperature recorded in previous time steps as regressors. In its current state, the fuzzy controller is only driven by the indoor temperature forecasted by the NNARX module; no variations in indoor heat gains or occupants' clothing and behavior were considered for driving the controller.

The main goal of this paper is to demonstrate the effectiveness of the hybrid neuro-fuzzy approach and the importance of efficiently designing the temperature forecast model, especially with respect to the selection of the *order* of the regressor for each of the external and internal parameters used. Therefore, a differential entropy-based method was applied in this study, which provided good forecasting performances for the NNARX model.

1. Introduction

Considering that we spend more of our time indoors as we become more affluent, over the last few decades, the problem of indoor air quality in non-industrial environments (particularly in dwellings and offices) has gained significant importance in relation to the effects on human health. In fact, it is estimated that during a normal weekday (excluding holidays), we now spend over 90% of our time indoors [1]. The air quality in working environments, dwellings and open space urban environments, is increasingly perceived by the public as one determinant of quality of life. Moreover, poor indoor comfort has direct effects on user productivity and indirect effects on building energy efficiency [2,3].

Temperature control represents one of the strategies to attain individual comfort in indoor environments, although temperature is only one of the factors affecting the thermal comfort level. ISO regulation 7730 defines thermal comfort as "the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation" [4]. Moreover, the ANSI/ASHRAE 55-2010 standards define the thermally acceptable environmental conditions for the occupants of indoor environments and suggest temperatures[1] and airflow rates in different types of buildings and different environmental circumstances [5].

The operative temperature intervals vary by indoor location type. ASHRAE suggests temperature ranges and airflow rates in different types of buildings and different environmental conditions. For example, for a single office in a building (with an occupancy ratio per square meter of 0.1) in the summer, the suggested temperature range is between 23.5 and 25.5 °C; the airflow velocity is recommended to be 0.18 m/s. In the winter, the recommended temperature is between 21.0 and 23.0 °C with an airflow velocity of 0.15 m/s [6].

An index called the predicted mean vote (PMV) was proposed by Fanger [7] to predict the average vote of a large group of people on the thermal sensation scale. It depends on six factors: metabolic rate, clothing insulation, air temperature, humidity, air velocity, and

* Corresponding author. Tel.: +39 (0) 935536448; fax: +39 (0) 935 536951.
E-mail addresses: antonio.messineo@unikore.it, messineo.ingegneria@gmail.com (A. Messineo).

[1] Typically, the standard for thermal comfort is defined by the operative temperature, which is the average of the dry-bulb air temperature and the mean radiant temperature at a given place in a room.

0360-1323/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.buildenv.2013.10.020

mean radiant temperature. The PMV represents a subjective quantification of the comfort sensation of the occupants in indoor environments. Other variations of the PMV, e.g., the PMV_{NV} [8] and the PMV(SET*) [9], have also been developed. These variations are more appropriate for situations in which only natural ventilation (no air conditioning) is used.

The utilization of conventional approaches to assure indoor thermal comfort in buildings (e.g., on-off devices and timers with set temperatures, which do not vary dynamically with the temperature in the monitored thermal zone) causes significant energy consumption. Liu et al. [10] and Stoops [11] showed that guaranteeing thermal comfort can lead to high energy consumption, especially if an optimal combination of the various influential variables (i.e., air temperature, air velocity, air humidity and radiant temperature) is not achieved. In contrast, they demonstrated that extreme energy saving measures can act to the detriment of the thermal comfort, causing negative effects on human health.

Therefore, a correct identification of the relationship between environmental parameters and energy requirements linked to thermal comfort preservation is extremely important. Weather conditions certainly have an influence on this relationship [12–14]. However, they are not the only influential elements because internal heat gains, thermal insulation, natural ventilation, air infiltration and behavior of the occupants also play an important role, especially in hot and humid climates [15]. Not surprisingly, in terms of electricity consumption, total building energy consumption over the last few years was second only to the industrial sector in Sicily (Italy) [14], with industrial activities having high refrigeration needs playing an important role [16,17]. Moreover, in densely built areas, the high energy consumption of summer air conditioning and the consequential emissions to the atmosphere are certainly enhanced by the well-known urban heat island (UHI) phenomenon [18–20], which increases building cooling loads (especially during peak hours) and reduces the efficiency of air conditioning appliances [21]. Furthermore, the UHI also enhances the heat release during night hours (due to the high thermal inertia of construction materials), thus further increasing the required energy demand for cooling. It is therefore apparent that an appropriate temperature and humidity control strategy is important to improve the energy efficiency of a building-HVAC integrated system, still guaranteeing thermal comfort conditions for building occupants [22].

In this paper, the effect of air temperature and other weather parameters (e.g., relative humidity and wind speed) are considered to train a neural network model aimed at forecasting indoor temperature to feed a fuzzy controller, which has the ultimate goal of keeping acceptable indoor conditions from the thermal comfort point of view.

The main goal of this paper is to show the design of a suitable neural temperature predictor (especially concerning the *order* selection of the regressor) and present the overall architecture of the coupled neuro-fuzzy model.

2. State of the art

A large number of studies exist regarding assessing, creating and maintaining indoor comfort conditions for building occupants [23]. In addition to parameters including thermal–physical properties of building materials and architectural features of the building (e.g., orientation, layout, transparency ratio, and shape factor), satisfaction with the indoor environmental quality (IEQ) is influenced by individual characteristics and by physiological parameters, e.g., age, clothing and physical activity [24].

Several scientific papers have applied soft computing and machine learning techniques to weather parameter forecasts; some applications of fuzzy logic controllers (FLCs) of indoor thermal parameters also exist [25–28]. For example, a fuzzy proportional integral derivative (PID) controller was proposed by Calvino et al. [27] for the microclimate control of confined indoor environments. The PMV [4] was assumed to be the driving index for the control procedure. In Refs. [25], "comfort" was represented by a 3D fuzzy set in a fuzzy cube. The authors presented the structure of an FLC and proposed its parameters be tuned using genetic algorithms. The proposed system was able to successfully manage thermal and visual comfort, air quality and energy savings in an office building.

Furthermore, artificial neural networks (ANNs) have been widely used to forecast indoor and outdoor air temperature in building applications, sometimes coupled with fuzzy logic (FL) systems [29]. However, an extensive literature on the coupling of neural and fuzzy models for comfort evaluation is missing.

Mustafaraj et al. [30] compared an auto-regressive model with external inputs (ARX) and its neural network-based nonlinear counterpart (neural network auto-regressive with external inputs – NNARX) to forecast the thermal behavior of an office located in a modern building using internal and external weather data to forecast the dry bulb temperature and the relative humidity of the room at different time horizons (from 30 min to 3 h ahead). Both models yielded acceptable forecasts. However, the NNARX model outperformed the ARX because temperature and relative humidity are governed by nonlinear diffusion equations and the linear models are not capable of capturing the (nonlinear) system dynamics.

Soleimani-Mohseni et al. [31] applied an ANN model (a feed-forward multi-layer perceptron – MLP – trained using the Levenberg–Marquardt algorithm) and an ARX model to estimate the operative temperature in buildings. They similarly concluded that the nonlinear ANN model outperformed the linear ARX model.

Huang et al. [32] used a multiple-inputs, multiple-outputs (MIMO) ANN model (trained with Bayesian regulation to obtain the optimal regularization parameters) for the prediction of the zone temperature in a building. The model proved to be able to capture fairly well the intrinsic dynamics of the investigated system. Trained with data sampled on a 10-min time step, the model yielded mean square errors (MSEs) ranging from 0.118 °C to 0.258 °C and mean absolute errors (MAEs) ranging from 0.211 °C to 0.422 °C for a 2-days-ahead forecast.

Thomas and Soleimani-Mohseni [33] compared first and second order ARX and ARMAX models for two-steps-ahead[2] indoor temperature forecast with an auto-regressing moving average with external inputs (ARMAX) models and Box-Jenkin (BJ) models. They concluded that the BJ and ARMAX models gave nearly the same MSE and MAE values for test data as the ARX models when using models of the same order. However, the NNARX models always outperformed (in terms of the MAE) the ARX models.

Mechaqrane and Zouak [34] also presented a comparison between NNARX and ARX models used to predict the indoor temperature of a residential building. The NNARX model performance was significantly better than the ARX model.

Gouda et al. [35] applied a feed-forward MLP trained with the Levenberg–Marquardt algorithm to model the thermal dynamics of building space and heating system to predict indoor temperature 2 h ahead. They used singular value decomposition (SVD) to select the order of the predictor.

Argiriou et al. [36] developed an ANN controller consisting of a meteorological module, which forecasts the ambient temperature and solar irradiance, a heating energy switch predictor module and a module for indoor temperature definition. The controller was

[2] A two-steps-ahead prediction means 30 min ahead, since the sampling interval was 15 min.