An economical method to estimate the air temperature and humidity around buildings on long time scales

Xiaoshan YANG[1, 2], Lihua ZHAO[2]

[1] *College of Architecture,Nanjing Tech University,Nanjing 211800, China, yangx@njtech.edu.cn*

[2] *State Key Laboratory of Subtropical Building Science, South China University of Technology, Guangzhou 510640, lhzhao@scut.edu.cn*

15 June 2015

1. Introduction

The microclimate around a building, establishing through the interaction with the surroundings, is a significant factor affecting indoor environmental quality and building energy performance. Some simulation tools, such as ANSYS Fluent[1] and ENVI-met[2], are capable of modelling the microclimates at community scale. However, the computational cost for these CFD-based models is high since the complex geometric features of an urban fragment and the complicated physical processes are involved. Such CFD-based models are only suitable for the microclimate simulations on short time scales (a few hours or days). This study outlines a method to estimate the mean temperature and humidity of the air around a building on long time scales (a few months or a year).

2. Methodology

The urban microclimate results from the combined influence of the background weather conditions and the urban configurations at multiple spatial-scales —— from city scale to community scale. The scope of this study is limited to the community scale. For a specific community context, it can be assumed that similar microclimate patterns will present for the days which are meteorologically homogeneous. If the microclimates of the representative days of each weather type are obtained, it is possible to empirically estimate the general features of the microclimate on a long time scale. Thus, instead of directly simulating the microclimate of a specific community for a season or a whole year, we conduct the microclimate simulations for a limited number of the representative days of weather types. Then the microclimate data of the representative days is taken as a sample data set for the prediction of the microclimate over a long time span.

An objective classification methodology[3], consisting of a principal components analysis of selected climatic variables followed by a cluster analysis of the resulting component scores, is applied to the EnergyPlus weather (EPW) data[4] to group each day into a limited number of synoptic weather types. Then a representative day can be determined from each identified synoptic weather type based upon a minimized component score sum-of-squares criterion. The key to the success of the objective classification method is in the selection of climatic variables which characterize the day type. From the point of view of urban microclimate, the following ten climatic variables are selected as the indicators of a day: daily average dry-bulb temperature ($\overline{T_a}$), the amplitude of daily dry-bulb temperature (ΔT_a), daily average relative humidity ($\overline{RH}$), the amplitude of daily relative humidity (ΔRH), average wind speed during the daytime (07:00–18:00) ($\overline{V_{day}}$) and during the nighttime (19:00–06:00) ($\overline{V_{night}}$), the frequency of calm wind (f_{calm}) and prevailing wind ($f_{previal}$), daily average global horizontal solar radiation ($\overline{SW_{glo}}$), and daily average direct normal solar radiation ($\overline{SW_{dir}}$). The first four variables provide information about the heat and moisture property of the atmosphere. The diurnal wind speeds are divided into two periods (daytime and nighttime) considering that the average wind speed during the daytime is generally higher than that during the nighttime. The frequencies of calm and prevailing wind indicate the stability of the atmospheric states.

The next step is the application of the microclimate model ENVI-met to simulate the microclimate for each of the representative days to obtain the sample data. The climatic data of the representative days are taken as the background meteorological conditions of the ENVI-met simulations. Due to the high complexity of urban microclimate system and the high degree of correlation between the weather variables, the conventional regression methods are unworkable. Artificial neural network is a promising method to dealing with the complexity and non-linearity of urban microclimate system. In this study, the neural network ensembles approach[5] is being used to predict the mean air temperature and humidity around buildings for long time scales.

Figure 1 outlines the procedures of the proposed method: (1) an objective classification approach is used to identify synoptic weather types and the representative day of each weather type for the EPW data; (2) after inputting the district configurations (buildings, pavements, greeneries, *etc.*) in ENVI-met, the sample data for training neural network predictors is obtained by running the ENVI-met simulation for each of the representative days; (3) once the optimal neural network ensembles are constructed, the mean air temperature and humidity around the analyzed building for the whole studied period are predicted by taking the corresponding EPW data as inputs.

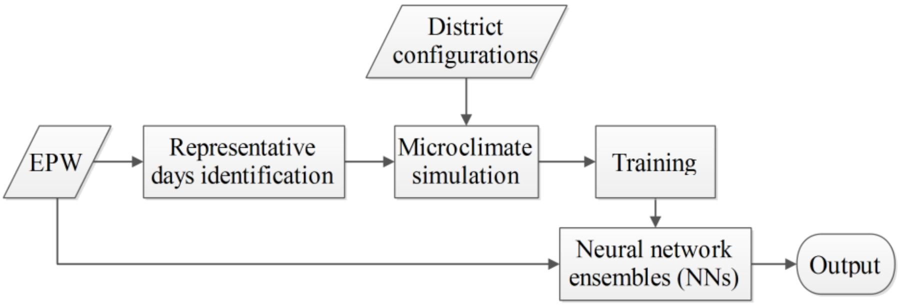

Fig. 1 The procedures for estimating the mean air temperature and humidity around buildings on long time scales.

3. Results

The objective classification method is applied to the EPW data for Guangzhou (23.13° N, 113.23° E), China, for the hottest period from 1 June to 30 September. Five synoptical weather types are identified for the period. Table 1 lists the average values of the ten climatic variables for the identified five weather types and the representative day of each weather type. The distinctive features of the five weather types are briefly summarized as follows:

- Type 1 — hot, large amplitude (Ta and RH), light wind, and quite strong solar radiation;
- Type 2 — high RH, small amplitude (Ta and RH), light wind, and weak solar radiation;
- Type 3 — very hot, high wind speed, stable wind direction, and strong solar radiation;
- Type 4 — high wind speed, very stable wind direction, and weak solar radiation;
- Type 5 — middle levels for almost all the climatic variables.

Table 1 Average weather data for the identified five synoptic weather types for Guangzhou (1 June – 30 September) and the representative day of each weather type.

Type No.	$\overline{T_a}$ (℃)	ΔT_a (℃)	$\overline{RH}$ (%)	ΔRH (%)	$\overline{V_{day}}$ (m/s)	$\overline{V_{night}}$ (m/s)	f_{calm} (%)	$f_{previal}$ (%)	$\overline{SW_{glo}}$ (W/m^2)	$\overline{SW_{dir}}$ (W/m^2)	Number of days	Representative Day
1	28.6	7.9	76	38	1.3	0.5	59	26	431	234	32	23 September
2	26.8	4.8	89	21	1.1	0.4	62	25	185	11	12	18 June
3	29.7	7.4	74	35	2.7	1.5	22	52	407	177	21	19 July
4	27.4	4.9	83	25	3.1	2.3	4	70	221	27	24	13 June
5	27.8	5.6	83	27	1.9	0.9	34	38	262	38	33	19 June

A case study was conducted to examine the effectiveness of the proposed method. A 150 m×150 m district with a row layout of buildings is modelled in ENVI-met, as shown in Figure 2. The building in the center of the district is selected as the target building for analysis. The settings of ENVI-met simulation are presented in Table 2. The mean air temperature and humidity around the studied building for the analyzed period estimated by the proposed method are compared with the results obtained by directly running the ENVI-met simulation for the entire studied period.

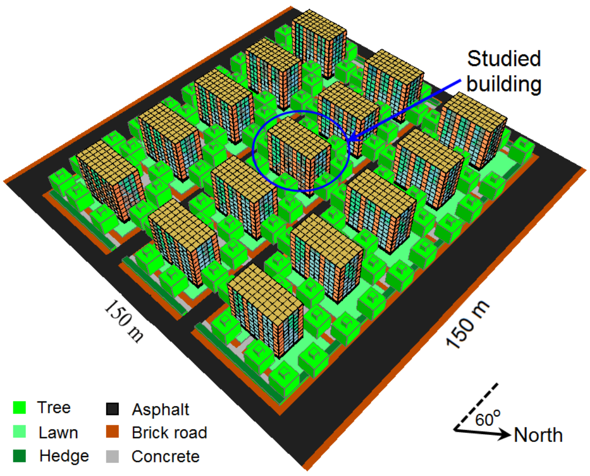

Fig. 2 The ENVI-met model.

Table 2 Settings of ENVI-met simulation.

Domain	150m × 150m × 50m
Meshes (size)	75 × 75 × 25 (dx=dy=dz=2 m)
Period	1 Jun. – 30 Sept./Representative days
Weather data	From the EPW File for Guangzhou
Plants	Tree: high 10m, clear 3m, LAD= 2 Hedge: high 1m, LAD = 2 Grass: high 0.4m, LAD=0.3
Ground	Asphalt: 8 cm thick, albedo 0.2 Concrete: 20 cm thick, albedo 0.23 Brick: 6 cm thick, albedo 0.15

Note: LAD—Leaf area density, m^3/m^3.

Figure 3 shows the mean air temperature and humidity around the studied building for the three days randomly selected from the analyzed period. Comparing the data from the direct ENVI-met simulation with the original EPW data, significant air temperature and humidity increases are found while the effect of microclimate is considered. That is mainly caused by the phenomenon of district heat island and the processes of evaporation or evapotranspiration from vegetation and soil surface. Acceptable agreements for both air temperature and air humidity are found between the direct ENVI-met simulation and the proposed method, with relative errors of less than 4% for temperature and less than 6% for humidity. That implies that the proposed method is a workable way for the estimation of the mean air temperature and humidity around a building on long time scales. And above all, for a normal PC, the computational time of the direct simulation approach is more than two months, while that of the proposed method is about 2 days. The comparing results indicate that the proposed method can significantly save computational time with relatively little loss in accuracy.

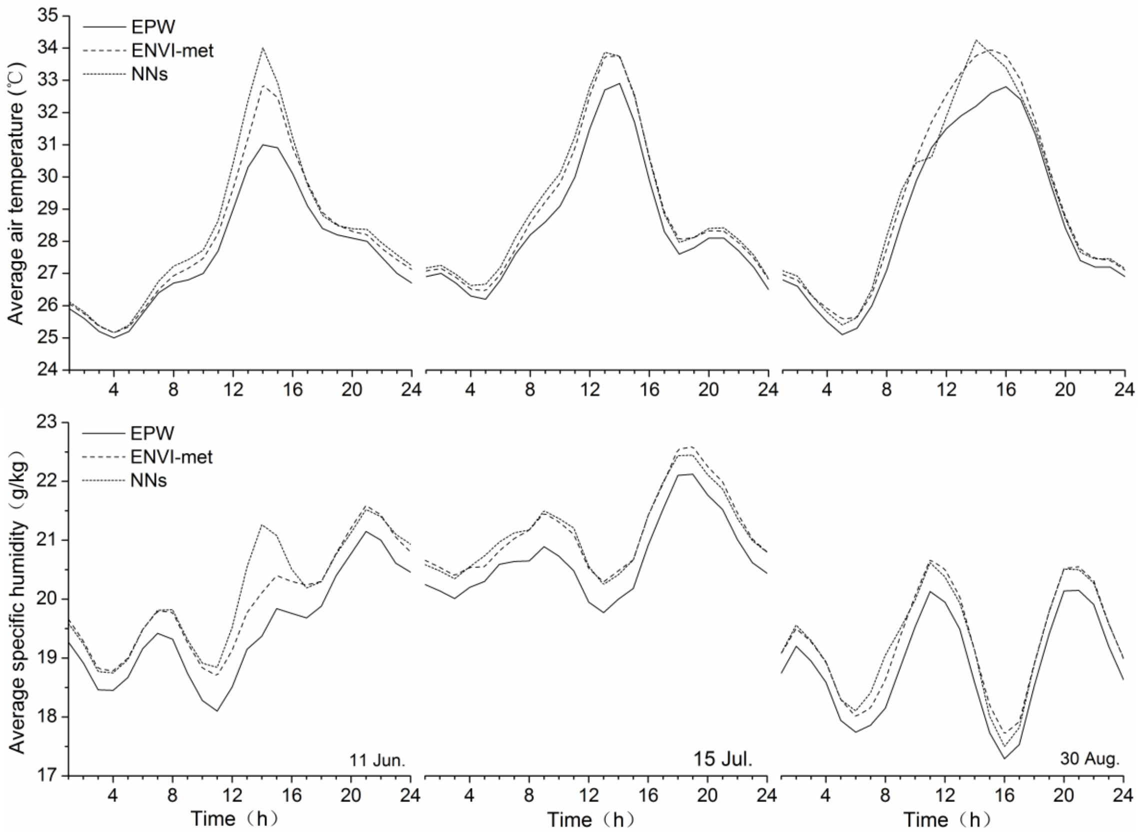

Fig. 3 Comparison of the mean temperature (top) and humidity (bottom) of the air around the studied building for the three randomly chosen days from the original EPW data (EPW), the direct ENVI-met simulation results (ENVI-met), and the results estimated by neural network ensembles (NNs).

4. Conclusion

A simulation-based method for estimating the mean temperature and humidity of the air around buildings on long time scales is outlined. The preliminary results illustrate that the proposed method can significantly save the computational time of microclimate simulations with relative errors of less than 4% for air temperature and less than 6% for air humidity.

Acknowledgment

This research is supported by National Natural Science Foundation of China (Project No. 51408303 and 51138004), the State Key Laboratory of Subtropical Building Science, South China University of Technology, China (Project No. 2015ZC12 and 2014KB21) and the Natural Science Foundation of the Jiangsu Higher Education Institutions of China(Project No. 14KJB560010).

References

[1] ANASYS, Inc. ANASYS Fluent, http://www.ansys.com/Products
[2] Bruse M. ENVI-met model, http://www.envi-met.com/
[3] Todhunter P.E., 1989: An approach to the variability of urban surface energy budgets under stratified synoptic weather types. *International Journal of Climatology*, 9, 191-201
[4] U.S. Department of Energy. EnergyPlus, http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_about.cfm
[5] Hansen L.K., Salamon P., 1990: Neural network ensembles. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(10), 993-1001