FUTURE HOURLY WEATHER FILES GENERATION FOR STUDYING THE IMPACT OF CLIMATE CHANGE ON BUILDING ENERGY DEMAND IN CHINA

Mingya Zhu[1], Yiqun Pan[1], Zhizhong Huang[2], Peng Xu[1], Huajing Sha[1]
[1]School of Mechanical Engineering, Tongji University, Shanghai 200092, China
[2]Sino-German College of Applied Sciences, Tongji University, Shanghai 200092, China

ABSTRACT

Future hourly Typical Meteorological Year (TMY) weather file is a prerequisite for utilization of building energy simulation software to estimate the impact of global climate change on building energy demand. On basis of Intergovernmental Panel on Climate Change - IPCC's latest predictions, this paper produces future TMYs of three representative cities in different climate regions in China from 2000 to 2089 including five time spans, in the form of EnergyPlus weather file format – EPW. With application of a statistical downscaling method – Morphing, estimated monthly climate change data, calculated by selected General Circulation Model (GCM) under Representative Concentration Pathways (RCPs, the latest future climate scenarios developed by IPCC in 2007), are integrated with local existing TMYs to achieve new TMYs' generation. Building energy demand by 2100 is predicted for three cities by using corresponding new TMYs as input of prototypical building models for annual energy simulation. Considering many uncertainties in IPCC's research, the predicted energy demand in Shanghai is revised by comparing predicted monthly weather data to observed data from 1961 to 2010.

Keywords: climate change, Typical Meteorological Year (TMY), building energy demand, building energy simulation

INTRODUCTION

Unequivocal warming trend of global climate is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and rising global mean sea level. As indicated in the Fourth Assessment Report (AR4,2007) of Intergovernmental Panel on Climate Change (IPCC), eleven of the last twelve years (1995-2006) are rank among the 12 warmest years in the instrumental record of global surface temperature (since 1850). Meanwhile average Northern Hemisphere temperatures during the second half of the 20th century are very likely higher than during any other 50-year period in the last 500 years and likely the highest in at least the past 1300 years. Model-based projections in AR4 shows that best estimates of globally average temperature change at 2090-2099, relative to 1980-1999, is 1.8~4.0℃ with possible range of 1.1~6.4℃ , under climate change scenarios in the IPCC Special Report on Emissions Scenarios in 2000 (called SRES scenarios). For the next two decades, a warming of about 0.2°C per decade is projected for SRES emission scenarios. Even if the concentrations of all greenhouse gases and aerosols have been kept constant at year 2000 levels, a further warming of about 0.1°C per decade will be expected due mainly to the slow response of the oceans. Even if greenhouse gas concentrations are to be stabilized, anthropogenic warming and sea level rise will continue for centuries due to the timescales associated with climate processes and feedbacks, emphasized (IPCC, 2007). Irreversible climate change has currently become one of the most serious and paramount challenges that mankind has to face. The global warming trend has great influence on the development of social, economic and ecological systems, especially on the rapid growth of energy demand and the increasingly dire environmental deterioration. How to reduce greenhouse gas emissions for effective moderation of climate change, meanwhile positively respond and adapt to possible consequences has become a common development objective around the world.

With the rapid rise of the proportion of building energy consumption in social energy consumption, building energy efficiency has become a top priority in the development of the construction industry, as energy saving and emission reduction has become a national responsibility. The construction area of new buildings per year from 2000 to 2005 was 1.6~2.0 billion m^2 in China (Kang, 2007). Obviously a golden age of building industry has been coming up, when building area increases significantly. However the building occupants' growing demands for comfort and functionality of building environment make this industry face opportunity and challenge in the meantime. Undoubtedly climate change would have significant influence on building energy demand. It is greatly necessary for construction industry to clearly understand the present situation and rationally response to global warming. An important premise of effective response is correct estimate of future trends of building energy demand influenced by climate change. In this way, reasonable development strategies and policies from a long-term point of view are possible. In this regard, building energy simulation software is an important tool. However, present hourly Typical Meteorological Year (TMY) weather files, used for annual building energy consumption calculation, are based on historical observations before 2000, which are not suitable for future building energy demand prediction. Consequently, the generation of future hourly weather data incorporating climate change estimation is an important prerequisite for trend projection of building energy demand, and also a key to discuss the impact of climate change on building energy demand.

The predictive study of future weather parameters has a history of nearly 20 years in the world and main approaches have been proposed: 1) General Circulation Model method, GCM is based on energy transfer mechanisms from atmospheric circulation to the land, sea and cryosphere. Only meteorology researchers can use this method. Meanwhile coarse resolution of GCM at present makes the simulation for regional climate has certain limitations and considerable uncertainty. 2) Stochastic weather model method, developing stochastic weather model based on historic observed data and simulating local climate change. This method requires researchers to be familiar with the stochastic variation of meteorological factors. (Van and Luo, 2002) 3) Statistic trend extending method, e.g. extrapolation of heating/cooling degree days, relatively simple and inaccurate. (Christenson et al., 2006) 4) Downscaling method based on GCM, including dynamical and statistical downscaling. Dynamical downscaling method makes GCM coupled with Regional Circulation Model (RCM) to estimate local climate change scenario. Statistical downscaling method achieves the combination of large-scale GCM outputs and separate regional observed data, which is widely used. A statistical downscaling method, called Morphing, was developed for generation of future houly weather files used in building performance simulation in 2005. Based on modeling outputs of a selected circulation model (named HadCM3) under SRES scenarios (climate change scenarios developed by IPCC in 2000) in UK Climate Impacts Programme (UKCIP02), the Morphing method was applied to generate TMY files of three representative cities in UK for three time slices: 2011-2040, 2041-2070 and 2071-2100, with the period of 1961-1990 as the baseline. (Belcher et al., 2005)

With the latest prediction of IPCC, this paper focuses on three representative cities in different climate regions in China, and forecasts future weather data besed on existing TMY files of the three cities. Here we apply Morphing, a time series adjustment method, to downscale monthly predictive results of selected GCM under different climate change path (Representative Concentration Pathways, RCPs - the latest climate change scenarios developed by IPCC in 2007), and integrates them with existing TMYs to obtain hourly TMY files in five future time periods for each city and climate change path. Then these TMY files are used as the weather inputs of prototypical building models developed with EnergyPlus for the trend prediction of building energy demand in typical cities by the end of 21^{st} century. Additionally the predictive results of Shanghai are revised by comparation of the GCM's monthly predicted outputs and observed weather data from 1961 to 2010 for more accurate assessment of building energy demand.

WEATHER DATA PREDICTION OF TYPICAL CITIES IN CHINA

Historical baseline weather data – existing TMY

The Finkelstein-Schafer (FS) method proposed by Hall in 1978 for hourly TMY generation is widely accepted. In this statistic method, a TMY consists of 12 typical meteorological months (TMM). TMMs are selected by comparing the cumulative distribution function (CDF) of each year with that of long-period composite (always 30 years). Measured by an index called *Finkelstein-Schafer statistic*, the closest month to the composite distribution is defined as a TMM. In the selection of TMM, there are four major weather parameters taken into account with certain weightiness: dry bulb temperature, dew point temperature, wind speed and solar radiation. (Chan et al., 2006)

Existing TMYs for China typical cities have three versions – CSWD (Chinese Standard Weather Data), CTYW (Chinese Typical Year Weather) and IWEC (International Weather for Energy Calculation), published on EnergyPlus website (http://apps1.eere.energy.gov/buildings/energyplus/), with different data sources and time spans of historical weather, as listed in Table 1, but consistently generated by FS method.

Future climate change scenarios

Climate change scenarios are applied to drive GCMs for prediction of future climate change. IPCC developed IS92 scenario, the first global scenario of greenhouse gas (GHG) emission in 1992. Then in 2000, SRES scenarios were developed. SRES includes four alternative development pathways, covering a wide range of demographic, economic and technological driving forces and resulting GHG emissions (IPCC, 2007). For preparation of Fifth Assessment Report (AR5), IPCC has developed new climate change scenarios – Representative

Concentration Pathways (RCPs), including four grades: RCP8.5, RCP6, RCP4.5 and RCP3-PD. RCPs means the prediction of time-evolving emissions or concentrations of radiatively active constituents, including a wide range of anthropogenic climate forcing. The number after "RCP" means the intensity of radiation forcing due to human activity by 2100, as listed in Table 2 (Moss et al., 2010). The larger radiation forcing will cause greater global warming. IPCC's Coupled Model Intercomparison Phase 5 (CMIP5) has published experimental outputs of many GCMs under RCP scenarios. These output datasets involve various weather parameters of all longitudes and latitudes around the world by Dec.2099.

Table 1 Comparison of different versions of existing TMYs for China typical cities

VERSION	CSWD	CTYW	IWEC
Developer	Tsinghua University & CMB[1]	ZHANG Qingyuan of TU[2] & Joe Huang of LNBL[3]	ASHRAE Research Project 1015
Historical weather data source	270 stations from CMB[1]	57 stations in China from NCDC[4]	DATSAV3 archived at NCDC[4]
Historical time span	1971-2003	1982-1997	1982-1999

[1]TU – Tsukuba University
[2]CMB – China Meteorological Bureau
[3]LNBL – Lawrence Berkeley National Laboratory
[4] NCDC – U. S. National Climatic Data Center

Table 2 Four types of RCP

NAME	RADIATIVE FORCING	PATH SHAPE
RCP8.5	>8.5W/m^2 in 2100	Rising
RCP6.0	~6.0W/m^2 at stabilization after 2100	Stabilization without overshoot
RCP4.5	~4.5W/m^2 at stabilization after 2100	Stabilization without overshoot
RCP3-PD	Peak at ~3.0W/m^2 before 2100 and then declines	Peak and decline

Trend prediction of climate change for typical cities

From the perspective of actively responding and adapting to climate change, it is necessary to analyze and understand the worst scenario of global warming. Among a large number of CMIP5 datasets, we choose output datasets of HadGEM2-CC model under the high-end path – RCP8.5 and a stable path – RCP4.5, to obtain large-scale climate change trends in Shanghai, Beijing and Guangzhou. Here, RCP4.5 is a stable-path contrast to the worst scenario – RCP8.5.

Future TMY generated by Morphing method need to be based on existing TMY. Mainly considering the available historical weather data, here in the three TMY versions for China typical cities we choose IWEC-version with the time span of 1982-1999, different to conventional baseline period (1961-1990), as the baseline weather condition. Then we divide the next 100 years into five periods: 2000-2017, 2018-2035, 2036-2053, 2054-2071 and 2072-2089, with the same time span as historical weather data, for the convenience of trend prediction.

Relative to baseline weather condition in 1982-1999, the changing trends of annual mean temperature under RCP4.5 and RCP8.5 for the three cities are different. As shown in Figure 1~3, by 2072-2089, annual mean temperature for three cities will increase 5.3 °C under RCP8.5, while 2.7~3.4 °C under RCP4.5. The increment of annual mean temperature under RCP8.5 is larger than that under RCP4.5 before 2053. Compared to 2036-2053, the rise of annual mean temperature in 2054-2071 is not obvious under RCP8.5. While after 2054-2071, annual mean temperature rises significantly in the three cities. Relatively annual mean temperature rises in a more stable manner under RCP4.5.

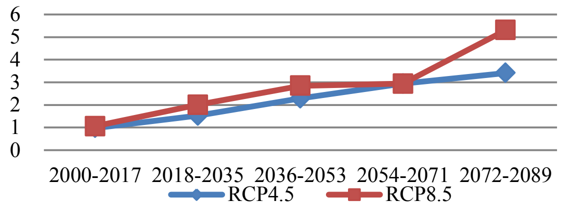


Figure 1 Annual mean temperature increase in Beijing (°C)

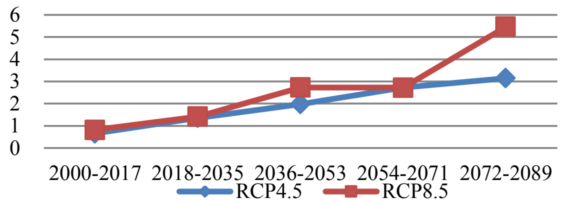


Figure 2 Annual mean temperature increase in Shanghai (°C)

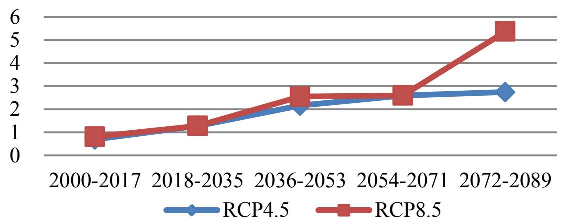


Figure 3 Annual mean temperature increase in Guangzhou (°C)

It is also of great significance to discuss the trend of monthly and seasonal mean temperature for building energy demand prediction. Figure 4~6 illustrate monthly average dry bulb temperature increase in five future periods in Beijing, Shanghai and Guangzhou under two climate change paths.

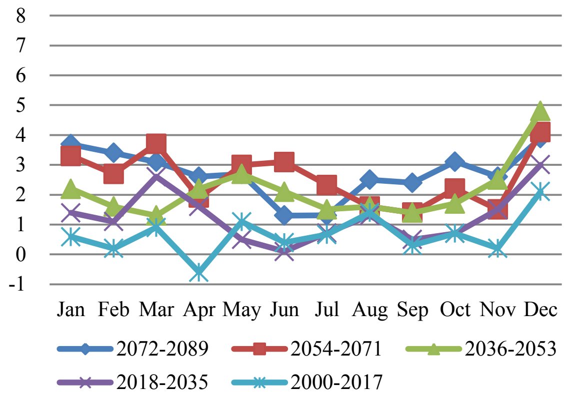


Figure 4(a) Monthly mean temperature increase under RCP4.5 in Beijing (°C)

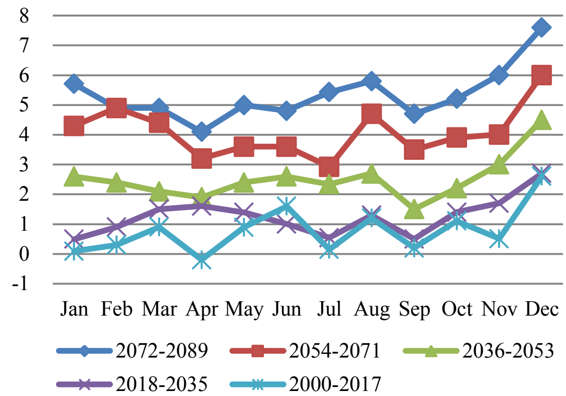


Figure 4(b) Monthly mean temperature increase under RCP8.5 in Beijing (°C)

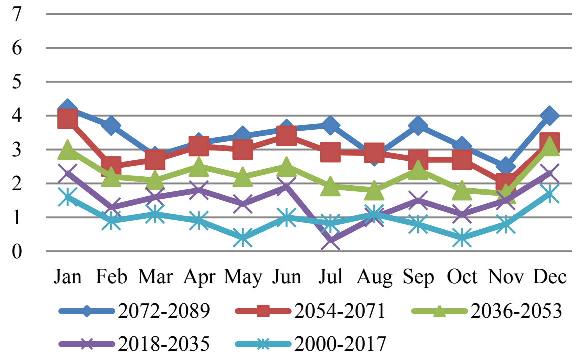


Figure 5(a) Monthly mean temperature increase under RCP4.5 in Shanghai (°C)

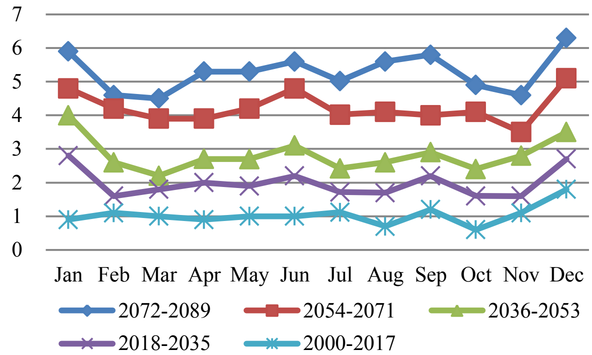


Figure 5(b) Monthly mean temperature increase under RCP8.5 in Shanghai (°C)

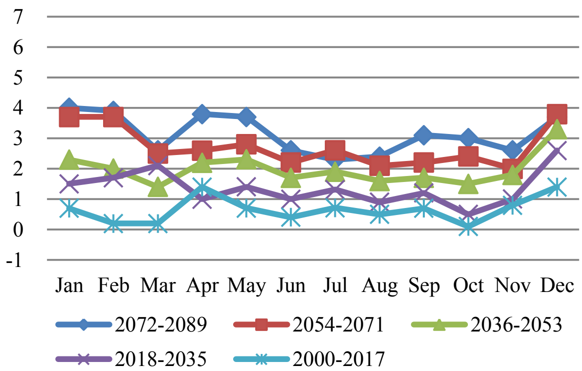


Figure 6(a) Monthly mean temperature increase under RCP4.5 in Guangzhou (°C)

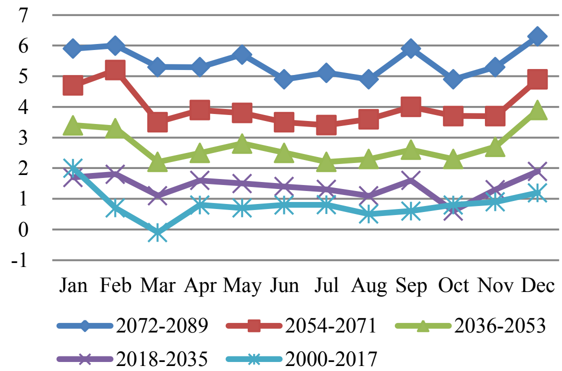


Figure 6(b) Monthly mean temperature increase under RCP8.5 in Guangzhou (°C)

During one year, the largest increase of monthly average temperature mostly occurs in winter, January or December, with a maximum up to 7.6°C in Beijing, and 6.3°C both in Shanghai and Guangzhou under RCP8.5 by the end of 21st century. Besides, the smaller increases of monthly average temperature often occur in summer and transition season, like from March to July and from September to November. Analysis of predicted temperatures shows that in Beijing there are larger differences of monthly average temperature increase among 12 months in a year as time goes on. By contrast, in Shanghai and Guangzhou, the trends of temperature rise month by month in a year are more steady, larger in winter and smaller in summer and transition season.

Morphing algorithms for new TMYs generation

Morphing, the time series adjustment method, modifies existing TMYs by synthesizing statistically downscaled results of GCM's large-scale outputs. It has been widely used by researchers from USA, UK, Australia, and HK for projections of local building energy demand. While in China Mainland, similar research is still few. For both climatically typical and economically developed cities in China, like Beijing, Shanghai and Guangzhou, the prediction of building energy demand have great significance of future urban energy planning and national/urban energy policy decision. By means of shifting and stretching, monthly mean data of predicted climate change are downscaled and combined with baseline time series of existing hourly TMYs. In this way, new TMYs both synthesis the climate change prediction and keep the physical characteristics of practical weather data.

The entire China is divided into 5 climate regions – very cold, cold, hot summer & cold winter, hot summer & warm winter and warm. Existing IWEC-version TMYs of Beijing (in the cold region), Shanghai (in the hot summer & cold winter region) and Guangzhou (in the hot summer & warm winter region) are separately local baseline weather condition. Additionally, the monthly mean data of predictive climate change, which is needed for application of Morphing, come from CMIP5's datasets. Selected datasets are outputs of a GCM named HadGEM2-CC under RCP4.5 and RCP8.5, and the datasets of the node nearest to target city are used.

In the process of applying Morphing for prediction of specific weather variables, the algorithm is not the same. For dry bulb temperature (dbt), Eq. (1) (Chan, 2011) is used:

$$\mathrm{dbt} = \mathrm{dbt}_0 + \triangle\,\mathrm{TEMPm} + \mathrm{adbt_m} \times [\mathrm{dbt}_0 - (\mathrm{dbt}_0)\mathrm{m}] \quad (1)$$

In Eq.(1), hourly predictive dry bulb temperature (dbt) is based on hourly temperatrure in existing TMY (dbt_0). $(\mathrm{dbt}_0)\mathrm{m}$ is monthly mean temperatrure of m month in existing TMY. dbt_0 is shifted by predicted change of monthly mean dbt in m month ($\triangle$ TEMPm) and stretched by the last item. The monthly stretching factor ($\mathrm{dbt_m}$) is calculated by Eq.(2) (Chan, 2011).

$$\mathrm{dbt_m} = \frac{\triangle\mathrm{TMAX_m} - \triangle\mathrm{TMIN_m}}{(\mathrm{dbt_{0max}})_\mathrm{m} - (\mathrm{dbt_{0min}})_\mathrm{m}} \quad (2)$$

In Eq.(2), $(\mathrm{dbt_{0max}})_\mathrm{m}$ and $(\mathrm{dbt_{0min}})_\mathrm{m}$ mean the monthly mean daily maximum and minimum temperature of m month in existing TMY. Then $\triangle\,\mathrm{TMAX_m}$ and $\triangle\,\mathrm{TMIN_m}$ mean the predicted changes of monthly maximum and minimum temperature.

While for dew point temperature(dpt), the situation is different. As a relative parameter, dpt reflects the saturation of the vapor in the humid air. And the value of dpt is based on both the dbt and the saturation of the humid air. In this regard, directly applying Morphing to predict dpt paremeter couldn't dispose of the noise impact of dbt. So an absolute parameter related to dpt is needed for projection of it. With these concerns, specific humidity (S) is predicted by Morphing, and then, dpt is calculated by hourly dbt and S. The algorithm for morphing S parameter is as Eq.(3) (Chan, 2011).

$$\mathrm{S} = \mathrm{S_m} \times \mathrm{S_0} \quad (3)$$

In Eq.(3), hourly specific humidity in existing TMY ($\mathrm{S_0}$) is morphed by monthly scaling factor $\mathrm{S_m}$, which is determined by Eq.(4) (Chan, 2011).

$$\mathrm{S_m} = 1 + \frac{\mathrm{SPHU_m}}{100} \quad (4)$$

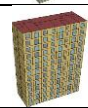
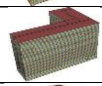
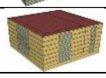
In Eq.(4), $\mathrm{SPHU_m}$ means predicted percentage changes in specific humidity of m month.

For each climate change path (RCP4.5/RCP8.5), new TMYs of five time periods (2000-2017, 2018-2035, 2036-2053, 2054-2071 and 2072-2089) are generated by morphing two major weather parameters - dbt and dpt, based on existing TMYs of three representative cities – Beijing, Shanghai and Guangzhou.

BUILDING ENERGY DEMAND PREDICTION

We use EnergyPlus to develop prototypical building models, referring to related design standards and survey data of existing buildings in three cities – Beijing, Shanghai and Guangzhou. The prototypical models, calibrated by investigated annual energy use data, can mainly reflect the general situation of different building types in the three cities. This paper focuses on four building types – high-rise office building, high-rise residential building, hotel and shopping mall, as shown in Table 3 and 4.

Table 3 Building information of prototypical models

TYPE	FLOOR	AREA	WWR*	SHAPE
High-rise office	12	19200 m^2	0.40	
High-rise residential	13	3262 m^2	0.14	
Hotel	12	23316 m^2	0.42	
Shopping mall	7 above, 1 under	33800 m^2	0.11	

*WWR – Window-Wall Ratio

Table 4 Heat transfer coefficient of prototypical building envelope (W/ (m^2•K))

TYPE	EXTERNAL ENVELOPE	BJ[1]	SH[2]	GZ[3]
High-rise office	Exterior wall	0.567	0.888	1.49
	Roof	0.569	0.638	2.7
	Window	2.67	2.67	2.951
High-rise residential	Exterior wall	0.538	0.928	1.658
	Roof	0.476	1.109	1.661
	Window	2.67	5.778	5.816
Hotel	Exterior wall	0.487	0.791	1.596
	Roof	0.485	0.552	1.547
	Window	2.902	2.959	2.951
Shopping mall	Exterior wall	0.531	1.304	1.5
	Roof	0.518	0.653	1.345
	Window	2.894	3.667	3.667

[1] BJ – Beijing, [2] SH – Shanghai, [3] GZ – Guangzhou.

Prediction of building energy demand under RCP8.5

Taken the worst climate change scenario into consideration, we choose TMYs generated under RCP8.5 for three typical cities in the last predictive period (2072-2089) as weather inputs of prototypical models for annual hourly energy simulation. Then we estimate the change of building energy demand by comparing above simulated results to the baseline, those calculated by using existing TMYs weather files as weather inputs.

As shown in Figure 7, energy consumption for heating will decrease and that for cooling will increase. For the situation of total energy consumption, in Beijing, the reduction of energy consumption for heating can offset most of the increase of that for cooling in office buildings, residential and hotels, which makes the change percentage of total energy consumption is not obvious, only about 1~3% added. Therefore, energy needs of buildings with large heating demand may have a trend of decreasing under global warming. While for shopping malls in Beijing, total energy consumption still has an increase of 6.8% by 2089, with cooling demand dominant in a year due to relatively more internal heat sources.

While in Shanghai, the proportion of heating energy consumption in total demand is small. Then the change of energy demand mainly comes from substantial growth of energy consumption for cooling. By 2089, the grow percentage of total energy consumption in residential, hotel and shopping mall buildings in Shanghai range from 18% to 20%, while smaller in office buildings, only 13%. Compared with office buildings, residential and commercial buildings need more energy consumption for cooling. Owing to longer running time and more cooling loads in residential and commercial buildings, the impact of temperature rise in summer on cooling demand are greater than that in office buildings.

By the end of 21st century, hotel buildings in Guangzhou have the biggest increase percentage of total energy demand, up to 28.6%, and 17~20% for office buildings and residential. Shopping malls have a smaller increase, only 7.7%. Except for shopping malls, other building types in Guangzhou have larger increments of energy demand than those in Shanghai. Located in hot summer & warm winter region, Guangzhou has higher winter and annual temperature, and the alleviative effect of winter warming to rapid energy demand growth in Guangzhou is very small. Therefore, regions with higher annual average temperature may have more increments of energy consumption influenced by climate change.

Sensibility analysis of building energy demand to climate change

In this paper, the sensibility of building energy

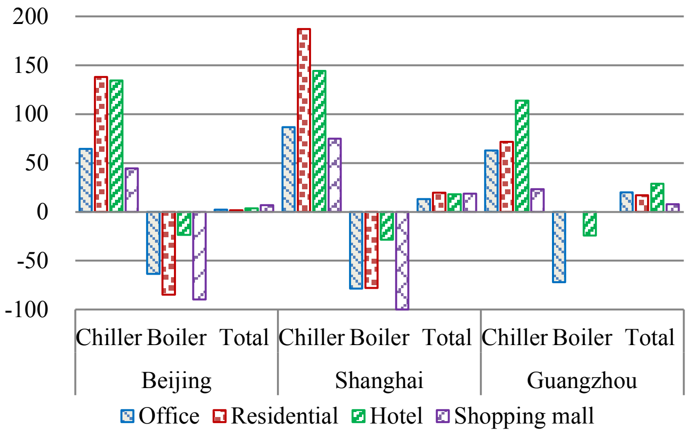


Figure 7 Change percentage of building energy consumption in 2072-2089 compared with 1982-1999 under RCP8.5 (%)

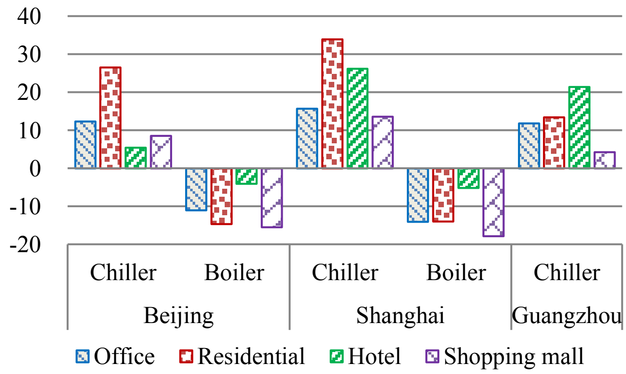


Figure 8 Change percentage of building energy demand per 1°C rise of seasonal average temperature in 2072-2089 compared with 1982-1999 under RCP8.5 (%)

demand to temperature rise is reflected by the ratio of heating/cooling demand change percentage to winter/summer seasonal average temperature rise in 2072-2089 under RCP8.5 compared with the baseline period (1982-1999), see Figure 8.

Under the condition of winter warming, the sensitivities of heating demand to temperature rise in all kinds of buildings in Beijing are separately similar to those in Shanghai. In the two cities, the reduction percentage of heating demand per 1°C temperature rise is 10~15%/1°C in office and residential buildings, and above 15%/1°C in shopping malls. The percentage in hotels is smaller, only 5%/1°C. The difference of energy demand sensibility in different building type may relate to different system type of HVAC mainly used in corresponding building type. For office, shopping mall and residential, centralized heating system is commonly used. The increases of local outdoor temperature influenced by global warming make heating period shorten, causing shorter runtime of centralized heating system during one year. Then energy consumption for heating reduces obviously because of centralized operation management depending on outdoor temperature.

While for hotel, distributed or semi-central air conditioning system is common to satisfy the operational and use flexibility. Thus, the shortening of heating period has smaller effects on reduction of heating demand.

Compared with Beijing and Guangzhou, all kinds of buildings in Shanghai have higher sensitivities of cooling demand to temperature rise in summer. Even they all have similar seasonal temperature rise, 5.2~5.5^{o}C, while in Guangzhou, the baseline of cooling demand in 1982-1999 is much larger than in other two cities, and the change percentages are relatively smaller. The increase percentage of cooling demand per 1^{o}C summer temperature rise in office buildings is 12%/1^{o}C in both Beijing and Guangzhou. The energy demand sensitivity of hotel to summer temperature rise in Guangzhou is far higher than that in Beijing. While for residential and shopping mall buildings, the situation is contrary. In the comparison between Beijing and Guangzhou, separately located in cold and hot summer & warm winter region, the energy demand sensitivities of office buildings are similar, while the energy demand sensitivities of hotel and residential, shopping mall are different. It seems that energy consumption for cooling at night may be the main part of cooling demand in summer in both Beijing and Guangzhou. There may have two reasons synthetically causing the sensitivity difference of hotel and residential, shopping mall. 1) The seasonal average temperature in Guangzhou is 3.5^{o}C higher than in Beijing in 2072-2089. 2) Under global warming, high insulation of building envelope in Beijing may be a burden to cooling supply.

Revision of energy demand prediction in Shanghai by observed weather data

While in IPCC's research, there are some key uncertainties. About the observed changes in climate, climate data coverage remains limited in some regions and there is a notable lack of geographic balance in data and literature, with marked scarcity in developing countries. Additionally, uncertainty in the equilibrium climate sensitivity, difference of GCM's estimates of different feedbacks in the climate system, and aerosol's uncertain impacts on the magnitude of the temperature response make IPCC's prediction not robust.

In consideration of the uncertainties in IPCC's prediction, the above predictive results of energy demand change in Shanghai are modified by comparison of monthly GCM-predicted and observed weather data from 1961 to 2010 for more accurate assessment of building energy demand. The observed weather data of Shanghai comes from U.S. National Climatic Data Center and the data are recorded by local airports.

By analysis of data shown in Figure 9, on average, the simulated temperature is 1.6^{o}C higher than observed mean temperature in winter, 2.6^{o}C lower than that in summer, and 1.2^{o}C lower than that in transition season within the past 50 years in Shanghai. This means that IPCC may overestimate the warming degree in winter, while underestimate that in summer. The product of the above seasonal temperature corrections (^{o}C) in Shanghai and corresponding energy demand sensitivity (%/^{o}C) are the corrections in change percentages of energy demand for different building types.

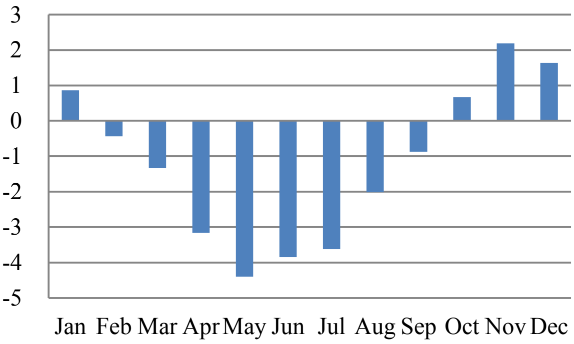


Figure 9 The average difference between monthly dbt calculated by GCM and observed monthly dbt from1961 to 2010 in Shanghai (^{o}C)

In this case, actual energy demand in the future will be more than we predicted based on GCMs' outputs. Figure 10 shows the comparison of previous and revised prediction change in 2072-2089 based on energy demand situation in 1982-1999. For four building types, actual increase percentages of cooling energy consumption are larger, while reduce percentages of energy consumption for heating are smaller.

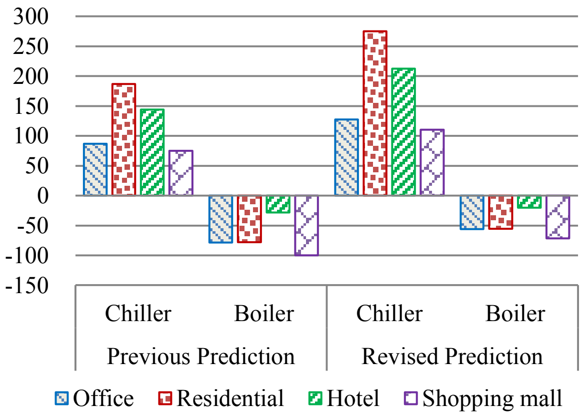


Figure 10 *Revised change percentages of building energy consumption in 2072-2089 based on baseline weather situation under RCP8.5 in Shanghai (%)*

CONCLUSION

With application of a time series adjustment downscaling method – Morphing, this paper produces future TMYs of three typical cities (Beijing, Shanghai and Guangzhou) in China for five future periods (2000-2017, 2018-2035, 2036-2053, 2054-

2071 and 2072-2089), integrating IPCC's latest experimental results under RCP scenarios to existing hourly TMYs. Future monthly weather data gives the situation of climate change for the typical cities. Under the stable path, RCP4.5, the rise of annual average temperature of the three cities is the same, about 3.0°C, and the temperature rise under the high-end path RCP8.5 is about 5.4°C. In a year, the largest increase of monthly average temperature mostly occurs in winter, and in summer and transition season, the rise is smaller.

We apply future TMYs generated under RCP8.5 in the last predictive period to prototypical building models for annual hourly energy simulation, and estimate the energy demand trends of three typical cities by the end of 21st century, with comparing simulated results calculated by new TMYs (in 2072-2089) and existing TMYs (in 1982-1999). Meanwhile, considering different characteristics of energy use in different building types (high-rise office building, high-rise residential building, hotel and shopping mall), here discusses the sensitivities of energy demand in different seasons to the rise of the corresponding seasonal average temperature.

By comparing monthly temperature predicted by GCMs with observed weather data from 1961 to 2010 in Shanghai, we guess that the winter warming may be overestimated and the summer temperature rise may be underestimated by IPCC, which means in the future actual energy consumption would be more than we predicted based on GCMs' prediction.

From the analysis of building energy demand changes, it is not hard to see that in different climate region, the pressure of building energy consumption growth may come from different aspects, and the sensitivities of energy demand to climate change for different building types are obviously different. In the development of building energy saving, it is an important premise that figuring out the primary contradiction of the energy use situation in specific building. Suitable energy efficiency measures in the sight of local condition and building type may be more effective. At the same time, decision makers need to propose and implement feasible energy policies, with local development trends of energy use considered. Above two aspects may be beneficial to slow down the substantial growth of energy demand and enhance the adaptability of building industry to the global energy crisis caused by climate change.

The impact of global climate change on building energy demand discussed in this paper is specific for different building type. However, this method can be applied to energy demand prediction of overall building sector when the construction industry structure is available.

NOMENCLATURE

dbt	=	dry bulb temperature
dbt_o	=	dry bulb temperature in existing TMY
$\triangle TEMP_m$	=	predicted change of monthly mean dbt in m month
$adbt_m$	=	monthly stretching factor of dbt
$\triangle TMAX_m$	=	predicted changes of monthly maximum temperature
$\triangle TMIN_m$	=	predicted changes of monthly minimum temperature
$(dbt_{omax})_m$	=	monthly mean daily maximum temperature of m month in existing TMY
$(dbt_{omin})_m$	=	monthly mean daily minimum temperature of m month in existing TMY
dpt	=	dew point temperature
S	=	specific humidity
αS_m	=	monthly scaling factor of S
S_o	=	specific humidity in existing TMY
$SPHU_m$	=	predicted percentage changes in specific humidity of m month

REFERENCES

Belcher, S.E., Hacker, J.N., Powell, D.S. 2005. Constructing design weather data for future climates. Building Services Engineering Research and Technology, 26(1):49 - 61.

Chan, A.L.S. 2011. Developing future hourly weather files for studying the impact of climate change on building energy performance in Hong Kong, Energy and Buildings, 43, 2860 - 2868.

Chan, A.L.S., Chow, T.T., Fong, S.K.F., Lin, J.Z. 2006. Generation of a typical meteorological year for Hong Kong, Energy Conversion and Management, 47(1):87 – 96

Christenson, M., Manz, H., Gyalistras, D. 2006. Climate warming impact on degree-days and building energy demand in Switzerland, Energy Conversion and Management, 47, 671- 686.

IPCC 2007. Climate change 2007: the physical science basis. Contribution of Working Group I to the fourth assessment report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kang, Y.B. 2007. Analysis of building energy efficiency meansures for energy conservation goal in the 11th-Five-Year Plan(1), Energy of China, 29(1):13 - 21.

Moss, R.H., Edmonds, J.A. et al. 2010. The next generation of scenarios for climate change research and assessment, Nature, 463(7282):747 - 756

Van Paassen, A.H.C., Luo, Q.X. 2002. Weather data generator to study climate change on buildings, Building Services Engineering Research and Technology, 23(4):251- 258.