Combined GIS, CFD and Neural Network Multi-Zone Model for Urban Planning and Building Simulation

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Abstract

This study developed a methodology using Geographic Information System (GIS), Computational Fluid Dynamics (CFD) and neural network to help predict the microclimate of the building. The geographic representation of an urban area in Syracuse generated in GIS was converted to the computational domain used in CFD simulation. The flow field around the building was simulated using the CFD model under different wind speeds and directions. Results from CFD simulation could be well presented in GIS using anchored coordinate system. The flow patterns were very similar when the wind speed was varied, while they were highly dependent on the wind directions. However, predicting the flow fields of different wind directions requires running the CFD simulation for each case. A neural network for machine learning was adopted to help predict the microclimate around the building so that much time can be saved. The results show that the proposed neural network has the potential to help predict the microclimate. The predicted microclimate could be used for further study of the building performance.

Introduction

A microclimate is defined as a local set of atmospheric conditions that differs from the general climate conditions, which is a statistic time- or spatial-averaged condition for a region or district. It can be as small as a few square meters or as large as many square kilometers (Wikipedia 2016). The microclimate in the urban area can be very different from the climate in the rural area where the weather data is usually collected. The air temperature is raised by the urban heat island effect, and the wind speed is reduced due to the sheltering of the buildings (Allegrini, Dorer, and Carmeliet 2012). In urban areas, the performance of a building is always affected by the microclimate around it, including temperatures, air velocities, and the pollutant concentrations. For example, the temperature in Athens was raised by more than 10 K due to heat island effect which may double the energy demand for building cooling (Santamouris et al. 2001). So understanding and being able to predict the microclimate around the buildings can help us design and improve the performance of the building (Erell, Pearlmutter, and Williamson 2012).

With the knowledge that microclimate significantly influences the performance of the building, how to determine the microclimate of the building is crucial. So far, most of the researchers or software which do the building performance studies used general climate conditions, which is usually measured in rural areas, like energy plus. These conditions might be valid on a large scale, like for a city, but not sufficient on a building scale. This paper presents some preliminary work of using Geographic Information System (GIS) and Computational Fluid Dynamics (CFD) together with the neural network to simulate and help predict the microclimate around the building.

GIS is a system that can be used to capture, store, manipulate, analyze, manage, and present data related to the positions on the earth's surface. Using the GIS, people can compare the geographic distribution of different information and discover how they relate to each other. A big advantage of the GIS is that it accepts many kinds of data and no matter what their source and original format is, they could be presented in a single map (National Geographic Society 2016).

CFD is a simulation technique that predicts the flow field and parameters in it by solving a series of fluid mechanic equations. This technique has been proven to be helpful in modeling the airflow for both indoor and outdoor space. Many studies on urban ventilation have been done using CFD (van Hooff and Blocken 2010; Luo and Li 2011; Yuan and Ng 2012).

Methods

The microclimate is defined as the thermal and aerodynamic conditions, which includes air temperature, humidity, air-borne contaminant concentration, wind velocity, and radiation. But this paper only focused on temperature and wind velocity around the building, which affect the performance, such as heat transfer and ventilation, of the building most significantly. To obtain it, this study proposed a method consisting of three steps (Figure 1):

1) combine GIS and CFD to construct a database of the microclimate under different wind conditions and use this database to train a neural network to help fast predict the microclimate;
2) use the trained neural network together with the known meteorological conditions to predict the microclimate (temperature and velocity field) around the building;
3) use the predicted microclimate to evaluate the performance of the building.

This paper is mainly focused on the first and second steps.

Computational Domain

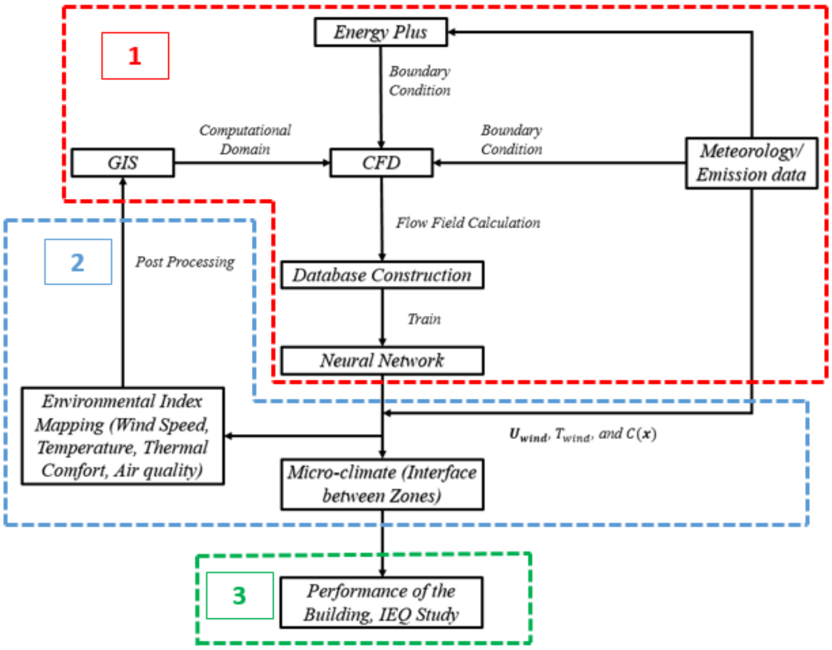


Figure 1 Schematic of the work flow

Generating a computational domain of an urban district is always difficult, and the difficulty increases with the area of the district. Previous researchers usually created the domain using some simplified geometry to represent the buildings. It requires gathering the dimension of the building and streets as well as reproducing them in some computer-aided design (CAD) software. This process becomes even more complicated when the district includes elevated ground surfaces.

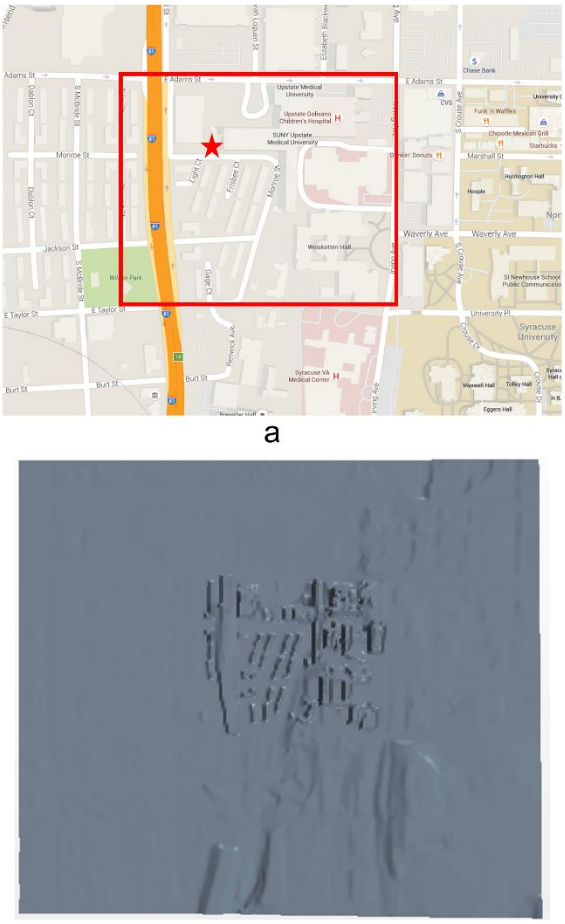
The Geographic Information System contains all the geographic data which is necessary for generating the computational domain, such as the width of the streets, the altitude or elevation, and the location and dimension of the buildings. Using GIS to generate the computational domain can not only make the work simpler but also make it possible to reload the data back into the GIS for geographic analysis after the simulation.

The target district of this study was a 500 m × 400 m urban area right in the center of the city of Syracuse in New York State in U.S.A. (Figure 2a). A map file of the target district was generated in GIS, and by using some data formatting software, the file was converted to Stereolithography (.stl) format, which can be used to generate mesh grids in CFD software (Figure 2b).

Using the .stl file generated above, the computational domain for CFD simulation was created (Figure 3). The domain consists of the target district including all the buildings, streets and highway in the center and an ambient region with only the ground surface, which is for flow to develop. The size of the ambient region is determined by expanding the edges from the target district by one unit of the target district in all the four directions. The height of the domain is 380 m, which was five times of the height of the highest building.

CFD Simulation

The CFD simulation in this work consists of two parts. The first part is to test the influence of wind speeds on the microclimate around the building. Moreover, the second part was to investigate the influence of the wind directions.



a

b

Figure 2 Target district generated in GIS (a. Location of the target district; b. STL file representing the target district)

Figure 4 shows the mesh used in the CFD simulation for predicting the microclimate around the building. It divided the domain into an ambient region, a core region and a region around the target building (shown as a red star in Figure 2b). The condition on the interface between the target building and the core region was used as microclimate in this work.

Figure 3 Computational domain for CFD simulation (1. West; 2. North; 3. East; 4. South; 5. Top; 5. Bottom)

The minimum surface cell size in the three regions are respectively 6m/1m/0.2m. The total mesh size is 4.2M. A commercial CFD software STAR-CCM+ was used in this study. The flow field was calculated as the constant density gas with the Boussinesq assumption based on the standard $k-\varepsilon$ turbulence model. All the equations were solved with the SIMPLE algorithm and a second-order accurate scheme. Radiation was included in the calculation.

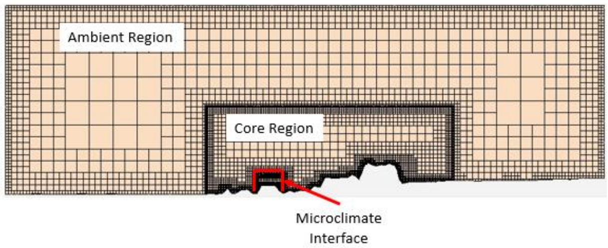


Figure 4 Mesh for CFD simulations

The baseline case was wind blowing from the west at 1 m/s speed. Cases of different levels of wind speed, 0.05 m/s, 0.25 m/s, 0.5 m/s, 2 m/s, and 4 m/s and cases of the wind blowing from 7-, 8-, 10- and 11-o'clock direction were simulated. The ground surface was always assumed at 30 °C, and the wind temperature was assumed to be 20 °C to represent the typical summer condition in Syracuse.

Neural Network

Since the general outdoor climate varies in a wide range, it is not always possible to simulate all the scenarios using CFD. This paper proposes to use neural network-based prediction to help predict the microclimate of the building. The neural network used in this work is called Feed-forward back propagation neural network, which is one of the most prevailing neural algorithms, for prediction of the microclimate of the building. To predict the nonlinear relationship between wind direction and three velocity components, we adopted the proposed artificial neural network (ANN)-based prediction algorithm.

Before it is used for prediction, the network was trained using known simulated data (the data from CFD simulations of different wind directions) and validated with the this known data. Afterward, with different inputs, the network should be able to predict the output of the new data set. This paper is only showing the results of validation.

Figure 5 shows the structure of the neural network for predicting the microclimate around the building under different wind directions. The network was trained using the five sets of data generated in the CFD simulations. The input vector includes three orthogonal coordinates and the wind direction. The output of our proposed neural network is the three velocity components and the temperature. During the training, we first normalized the training dataset using a baseline value to minimize the effect of the different scales of input data values. Each set of data in the input layer was called a neuron. Each neuron was transferred to the output layer by taking the inner product of the input and weight vectors. The neural network has two layers (the numbers of layers can be adjusted to increase the accuracy), each of which has four neurons respectively. At first, the weight was assigned randomly. After the first round of calculation, as a response to the errors, which are the differences between the target outputs and the actual outputs (from CFD calculation), the neural network updated the weights between the interconnected neurons during the training process. Specifically, the gradient descent algorithm with momentum weight and bias learning function was utilized in this study. The algorithm updated weights by calculating the weight change ΔW for a given neuron. The weight updating equation is provided as follows:

$$\Delta W = C_m \Delta W_{prev} + (1 - C_m) R_l G_w$$

where $\Delta Wprev$ is the previous weight change, R_l is the learning rate, C_m is the momentum constant, and G_w is gradient with respect to performance.

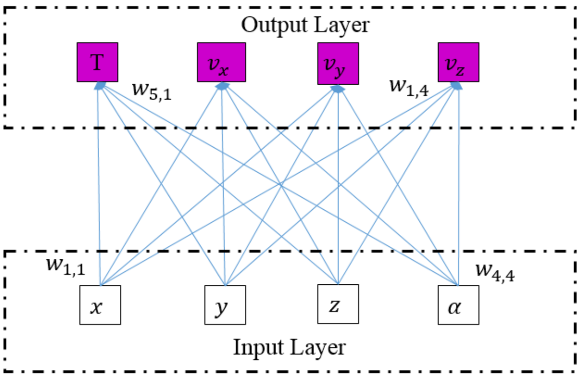


Figure 5 Neural network for predicting the microclimate around the target building under different wind directions

Results and Discussions

GIS Presentation of the Result

GIS has the advantage to present multiple kinds of information geographically and help find the relationship between them. Therefore, it provides a platform for the engineers to analyze the information for interdisciplinary investigations. This study used the ground geometry generated in GIS for CFD simulation and based on the anchored coordinate to import the CFD results back into the GIS. Figure 6 shows the temperature profile at an altitude of 10 m. Due to the elevation of the ground, there was a blank area at the southeast corner (No temperature data existing here). This figure shows that the results from the CFD simulation can be well presented in GIS.

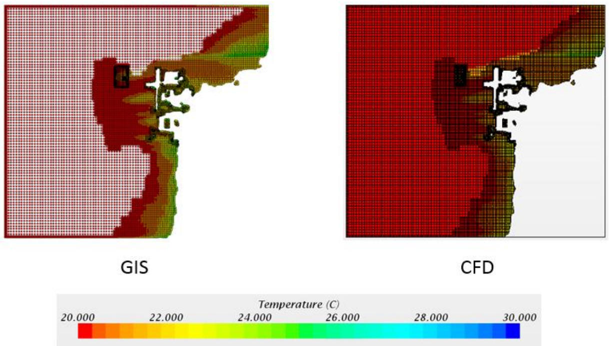


Figure 6 GIS Presentation of CFD Results

Effect of the Wind Speed

The velocity field of the microclimate was shown in Figure 7. Since the wind blew from the west, a clear wake region generated by the building in front of it was observed. Lower velocity existed in this region, and the shapes of the region seemed to be consistent in all the six cases. In order to confirm this similarity, dimensionless velocity was plotted by dividing the air velocity by the far-field wind speed. Figure 8 indicates that the flow fields of the microclimate under different wind condition were highly similar, which means that when the wind direction is fixed, the flow field of the different wind speed can be easily obtained by using the similarity.

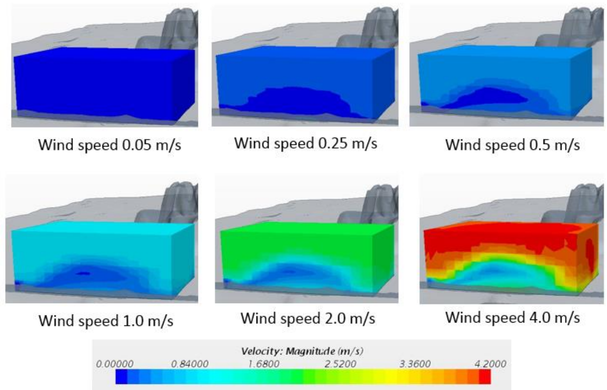


Figure 7 Velocity field of the microclimate under different wind speeds

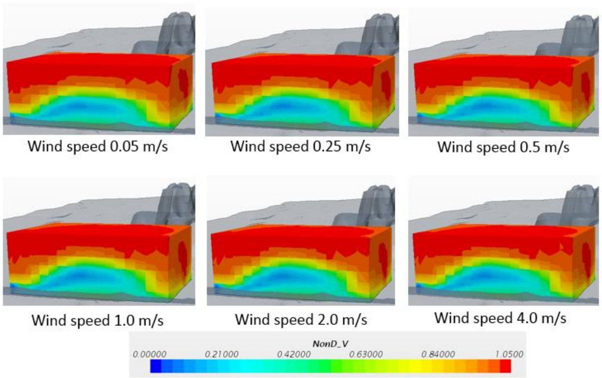


Figure 8 Dimensionless velocity field of the microclimate under different wind speeds

Effect of the Wind Direction

Different with the wind speed, the wind direction changed the flow field completely, both patterns and magnitude (Figure 9). Due to the existence of the surrounding buildings, when the wind blew from a different direction, different parts of the microclimate were contained in the wake streams of the surrounding buildings. When the wind direction was changed from the west to the north (0° to -60°), the wake stream of the building on the west side of the target building moved to the south. When the wind direction was changed from the west to the south (0° to 60°), the wake stream of the building on the west avoided the target microclimate, and the one of the buildings on the south started to affect the target microclimate.

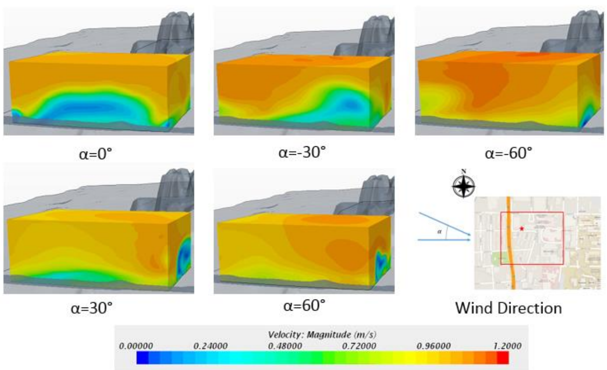


Figure 9 Velocity field of the microclimate under different wind directions

Neural Network Training and Validation

Since the wind direction always changes during a year and even during a day, it is not applicable to run the CFD simulation for every different angle. This work proposed to use a neural network to help predict the flow field of the microclimate when the wind blew from any directions. The network was trained and validated using the data generated in the previous section. The validation results were shown in Figure 10. It was indicated that the neural network was able to capture the flow pattern of the microclimate, although not the same. One explanation could be the neural network over-predicted the flow field, which can be improved by adjusting the structure of the neural network, for example, numbers of layers, numbers of neurons in each layer. Moreover, another explanation could be more data (more different wind directions) is needed to train the network.

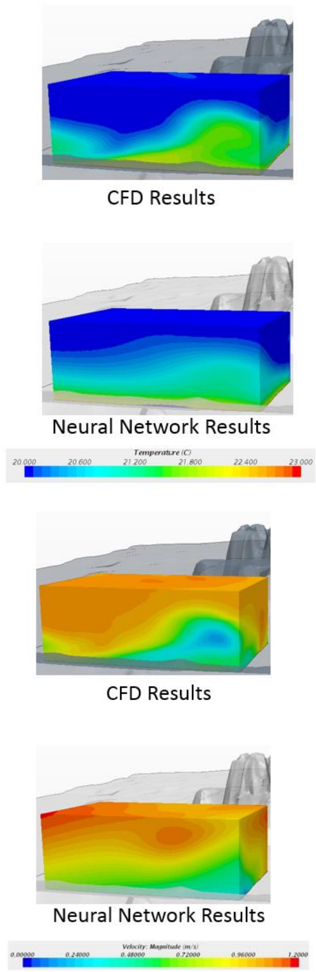


Figure 10 Validation of the neural network (α=-30°)

Conclusions

The microclimate has a direct impact on the performance of the buildings. General climate condition is not sufficient to represent it when the building is in an urban area. This paper utilized a method combining GIS and CFD to determine the microclimate and proposed to use a neural network to help predict it in a faster way. Some major findings of this paper were listed here:

1. GIS is a very powerful tool. Generating the computational domain using GIS for urban district simulation is simple.
2. The microclimate around the building was confirmed to be very different from the general climate condition.

3. The flow fields of the microclimate were dependent on the wind speeds, directions, and surrounding buildings.
4. The flow fields of the microclimate under different wind speeds were highly similar to each other.
5. Feed-forward back propagation neural network is being used for the prediction of the microclimate under different wind directions. The network was validated to be helpful, and the work of tuning the network is still ongoing.

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