BASIS STUDY ABOUT PREDICTION TO AIR FLOW ENVIRONMENT IN CROSS-VENTILATED ROOM BY NEURAL NETWORK

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ABSTRACT

In many parts of Asia as typified by Japan, conditioning of the indoor thermal and air environments using natural ventilation since ancient times. When indoor thermal and air environments are predicted, the use of simulation technologies such as CFD and Heating and Ventilation Network Model has increased. Those have advantages and disadvantages. In addition, AI programs like Neural Network (NN) and Genetic Algorithm (GA) are increasingly utilized in other research areas. In architectural equipment field, there are examples of air-conditioning system models with NN. These programs are relatively easy to use, finish the calculation quickly, and even conduct assessment and prediction. However, there are few application examples of NN in simulations of thermal and air environment of cross-ventilated room. This study examines fundamental investigations in the application of NN to cross-ventilation environmental simulation. As a result, it revealed that the results of the simulations with NN tended similarly to the results of CFD under the condition that 2 openings were open. Although, by the combination of the cases with 2 openings open, the simulation of NN with 3 openings in case, which had small calculation load and high simulation accuracy, gained low accuracy and basically resulted in similar wind directions to the results of CFD.

KEYWORDS

AI, Neural Network, Cross-Ventilation, Indoor air environment, Air velocity, Vectors

INTRODUCTION

In many parts of Asia as typified by Japan, conditioning of the indoor thermal and air environments using natural ventilation in the morning and night of summer since ancient times. Although the period which conditions indoor thermal and air environments with air-conditioner continued with the spread of air conditioners, the tendency that cross-ventilation will be taken in positively is increasing again in response to gain of energy-saving momentum in recent years.

When indoor thermal and air environments are predicted, the use of simulation technologies such as CFD and Heating and Ventilation Network Model has increased. Heating and Ventilation Network Model as represented by COMIS-TRNSYS regards a space as a mass point, and that it can conduct calculation about many spaces in a short time. However, we cannot figure out the detailed indoor airflow distribution through it (Fig.1). On the other hand, CFD, which has spread rapidly because of the advance in computation technology, can show the detailed indoor airflow distribution. However, its users are required specialist knowledge and experience in grid generation and in selecting calculation algorithm, difference scheme, turbulence model and various types of boundary conditions (Fig.2). CFD also needs computation time and costs severely.

In addition, AI programs like Neural Network (NN) and Genetic Algorithm (GA) are increasingly utilized in other research areas. These programs are relatively easy to use, finish the calculation quickly, and even conduct assessment and prediction. The followings are the simple overviews about these technologies.

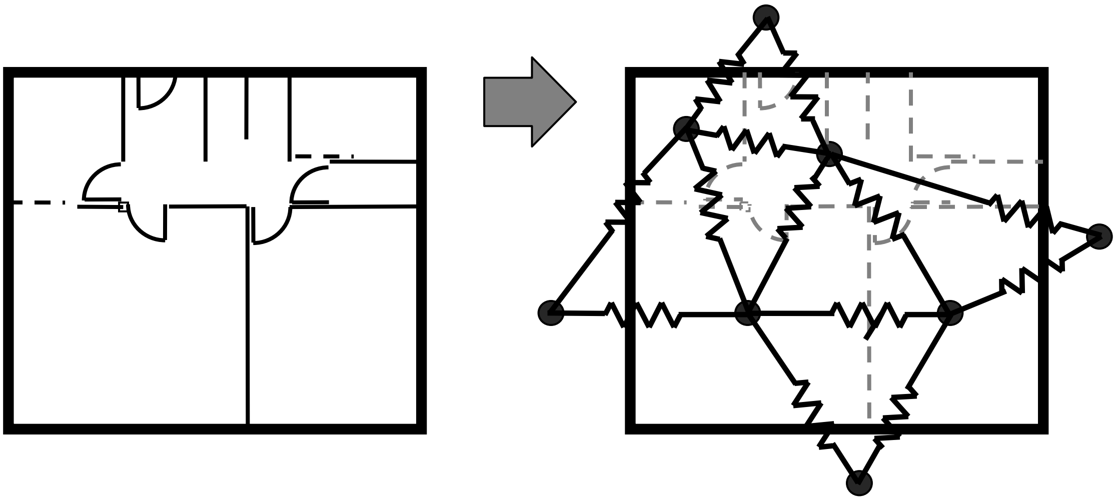
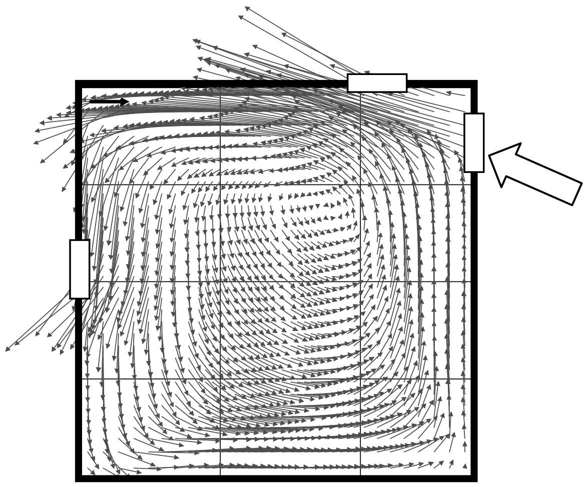


Figure 1. Network modell concept



Total Cell Number, Min. y+		?
Turbulence Model		?
Algorithm		?
Discretization Scheme		?
Boundary Condition	Inlet	?
	Outlet	?
	Walls	?

Figure 2. CFD concept

Genetic Algorithm (GA)

Living things generally repeat breading and produce offspring. The offspring receive the parents' genes, so they genetically have something resemble to their parents. A mutation evolution rarely happens and a new gene which has no relation to those of the parents appears. GA includes the variable like hereditary nature, crossover, and mutation causes. Gene sequences in GA are created by only two numbers, 0 and 1. GA is an AI that explores the best appropriate gene (a combination of 0 and 1) through the repetition of mutation evaluation and crossover that are mentioned above.

Tables are numbered. The table caption is below the table.

Fuzzy Theory

People frequently use adjectives of ambiguous meaning such as *tall, hot, many, heavy*. An ambiguous (fuzzy) quantity is hard to handle as “more than” and “less than” a numerical value. We can express such quantity by using of a gently shifting scale appropriate to it in Fuzzy Theory. An air conditioner which is equipped with the “fuzzy” function appeared years ago. This function enables computers interpret those ambiguous sense like “a bit cold” or “rather cold”.

Neural Network

Neural Network is AI model based on human brain function. Numerous brain cells called neuron are webbing in human brain. At each connecting part (axon), an excitement produce brain secretions and information is transmitted and learned (Fig.3). The presence or absence of information transmitting is determined by threshold level. It is the boundary of whether an excitement happens or not. In this way, AI is modelled based on human brain cells network and progresses learning by given information.

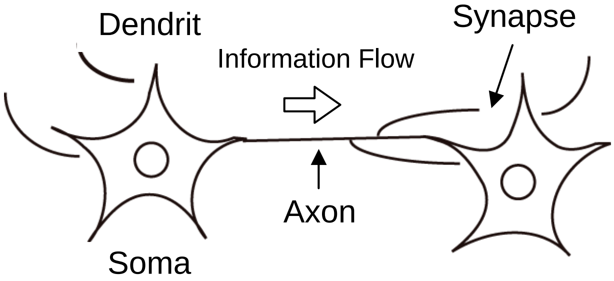


Figure 3. Neuron of Neural Network

PURPOSE OF THE STUDY

In architectural equipment field, there are examples of air-conditioning system models with NN [1]. But there are few application examples of NN in simulations of thermal and air environment of cross-ventilated room. So, this study examines fundamental investigations in the application of NN to cross-ventilation environmental simulation. Cross-ventilated indoor environment is greatly influenced by position and size of the openings, and wind direction and velocity outside of the room. Because of these variables’ interaction, a high-accuracy simulation needs CFD in each individual case. But it takes large amount of time and load in calculation. In this study, the purpose is prediction of cross-ventilated indoor environment under the condition that only position of openings and wind direction are changed, but size of openings and wind velocity outside of the room are in the same condition.

OUTLINE OF THE STUDY

The examination object in this study was a room shown in Figure 4, which is modelled from second level of a house. In the calculation model, eave height (5.9 meters) and eave wind velocity were normalized as 1 respectively. This model has 14 openings in all, but this study dealt with only 3 of them (Fig.5). The indoor airflow distribution at the case when these openings are opened was simulated with NN.

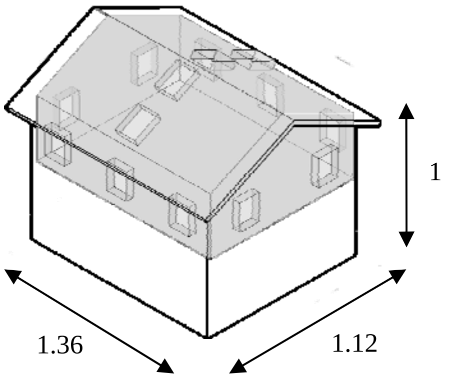


Figure 4. Object house

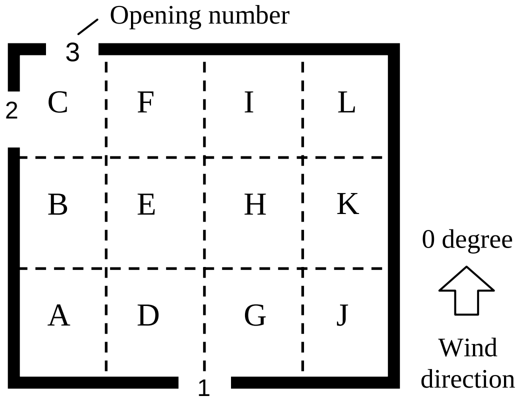


Figure 5. Object room

Some cases of wind directions were calculated in advance with CFD so that NN can learn the data. Then, the simulation of the target cases was calculated with NN. The room was divided 12 part areas as shown in Figure 5. The average value of x-way, y-way, and synthesized wind velocity (Eq.1) inside of each part were dealt with in the calculation (Fig.6).

$$V = \sqrt{{V_X}^2 + {V_Y}^2 + {V_Z}^2} \tag{1}$$

V : Synthesized wind velocity, V_X : Wind velocity of X direction, V_Y : Wind velocity of Y direction, V_Z : Wind velocity of Z direction

A room which is 1 meter (normalized value: 0.17) from the wall was defined as a residential zone (Fig.7). The average synthesized wind velocity was calculated, and it was divided by wind velocity at eaves to require the velocity rate. Then, the results of CFD and NN were compared to each other.

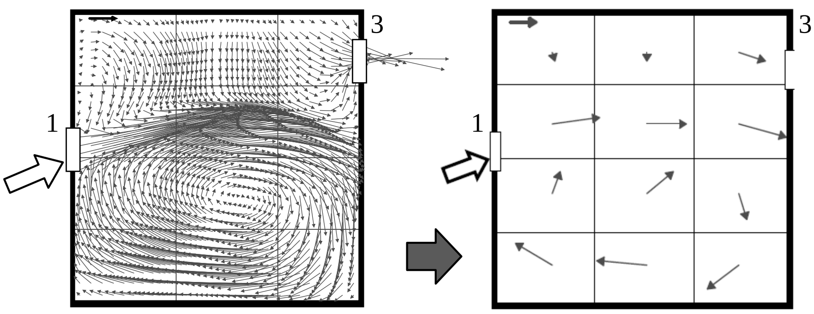


Figure 6. Wind velocity distribution in divided part areas

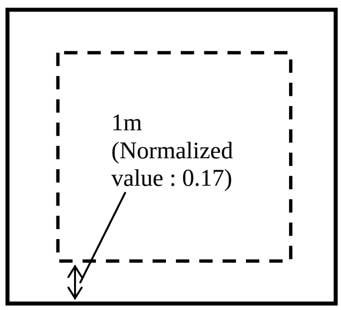


Figure 7. Residential zone

Fist, as shown in Figure 8, NN learned the indoor wind velocity distribution of 8 directions (0 to 315 degrees at intervals of 45 degrees). Then, NN predict the wind velocity distribution, wind direction, and average velocity in residential areas of another 1 direction. This case is called as Case 1.

Moreover, NN learned the results of CFD in which the opening 1 and 2, and the opening 1 and 3 were open respectively. Then, another simulation of the airflow distribution was conducted with all of the openings (1, 2, and 3) open. The learning patterns were considered with the following 3 cases (Fig.8).

Case 1: NN learned the distribution at the 8 directions, then simulate the distribution at another 1 direction.

Case 2: NN learned the distribution of 2 directions, then simulate the distribution at the in-between direction.

Case 3: NN learned the distribution of 4 directions, then simulate the distribution at the 1 direction (center of them).

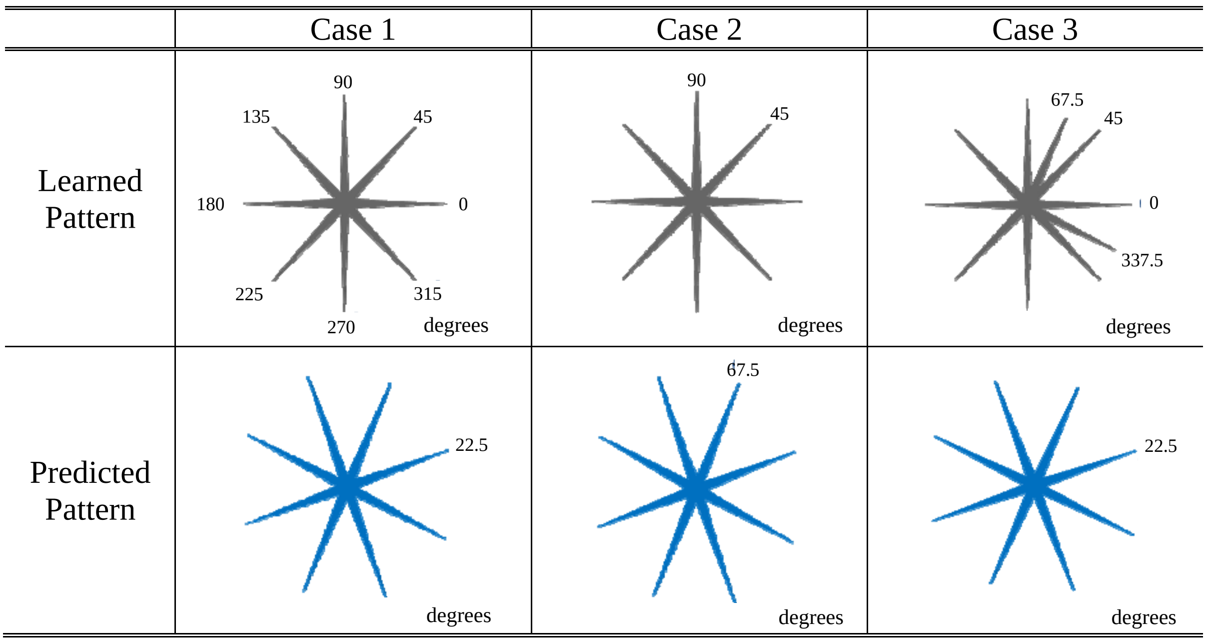


Figure 8. Learned and predicted patterns

ANALYSIS METHOD (CALCULATION CONDITION OF NN)

The connection weights between the input layer and the hidden layer were compressed as in Figure 9, and over 130,000 times repeated learning (130,000 times back propagation leaning) was conducted. In mid-course of the leaning, it was treated as convergent when the evaluative functional value was 0.001 and under. The multilayered Neural Network used in this study is applicable in many other areas, for example, a simulation of general nonlinear classification, and a tool of multiple nonlinear regression analysis. NN's leaning pace is fast enough and it is available with commonly-used personal computers.

For a highly accurate prediction, it is necessary to repeat leaning and prediction with sample answers and to reconsider the number of neurons in the hidden layer and the best value of the connection weights among the layers. After the consideration of the pretreatment with sample answers, the calculation in this study was conducted with the parameters in Table 1.

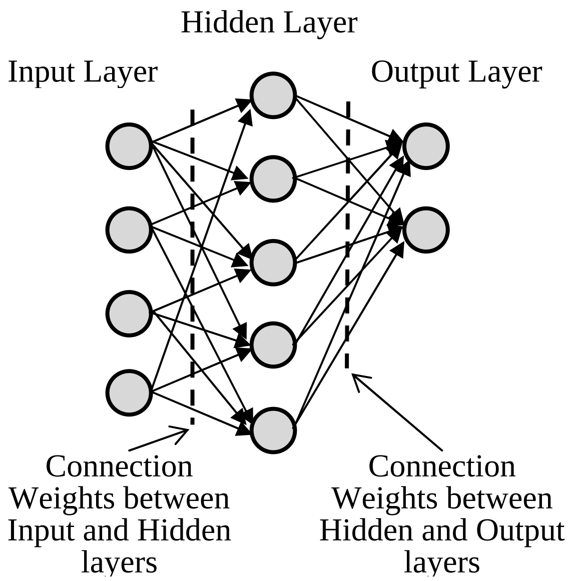


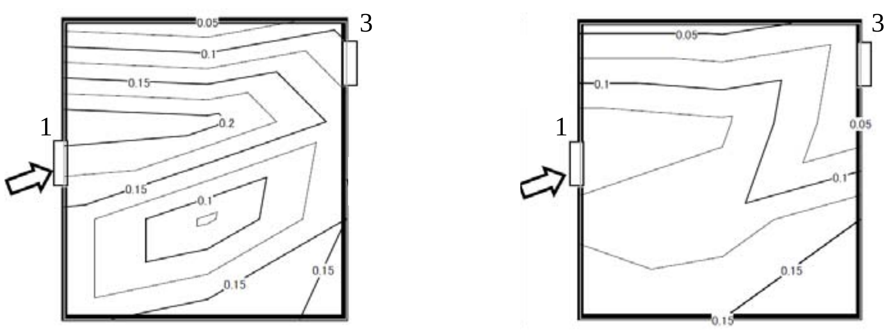
Figure 9. Layers and connection weights

The number of the hidden layers	25
The connection weights between input layer and hidden layer	0.75
The connection weights between hidden layer and output layer	0.25

Table 1. Parameteers of NN calculation

RESULTS AND DISCUSSION

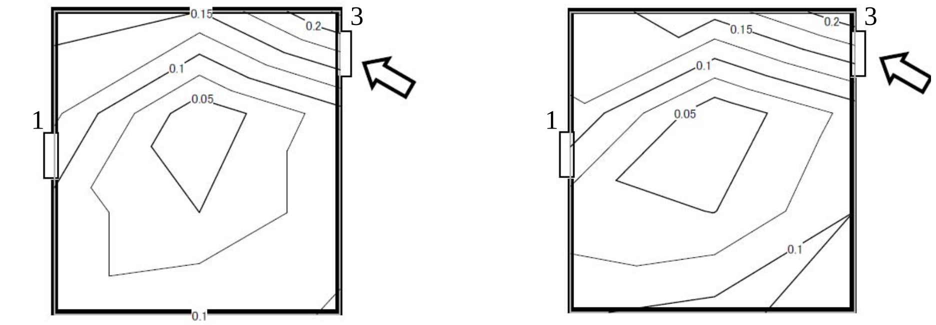
Figure 10, 11, 12 show the wind velocity distributions at 22.5, 157.5, 247.5 of the wind direction degree of Case 1. The result of CFD shows slightly higher values in some parts than those of NN's simulation. However, both of them generally showed the similar areas where equal wind velocities appear, and the similar damping pattern from inlet to outlet.



CFD

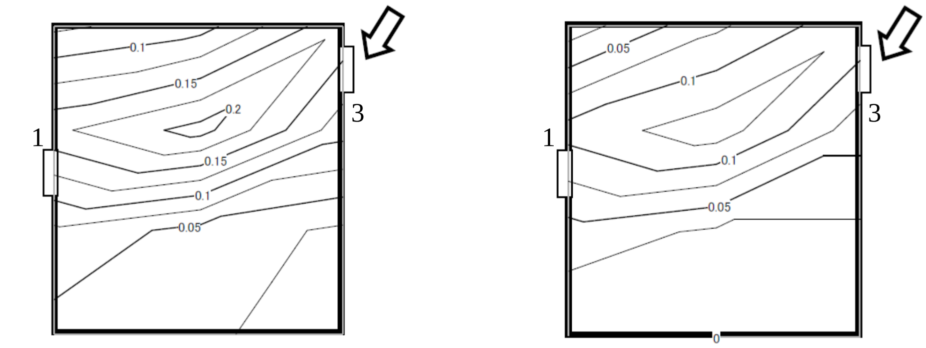
NN

Figure 10. Wind velocity distribution at 22.5 degree of Case 1



CFD NN

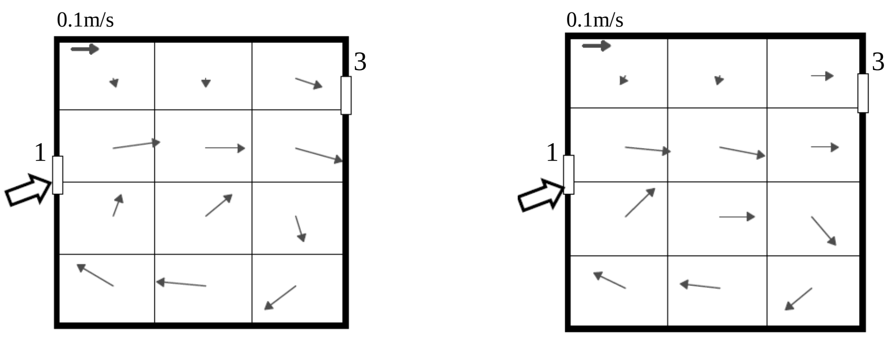
Figure 11. Wind velocity distribution at 157.5 degree of Case 1



CFD NN

Figure 12. Wind velocity distribution at 247.5 degree of Case 1

Figure 13, 14, 15 show the wind velocity vectors distribution at 22.5, 157.5, 247.5 of the wind direction degree of Case 2. The wind velocity vectors at the area which seemed to be the wind pathway were simulated with very high accuracy. Besides, the condition of the indoor airflow circulation was re-created well.



CFD NN

Figure 13. Wind velocity vectors distribution at 22.5 degree of Case 2

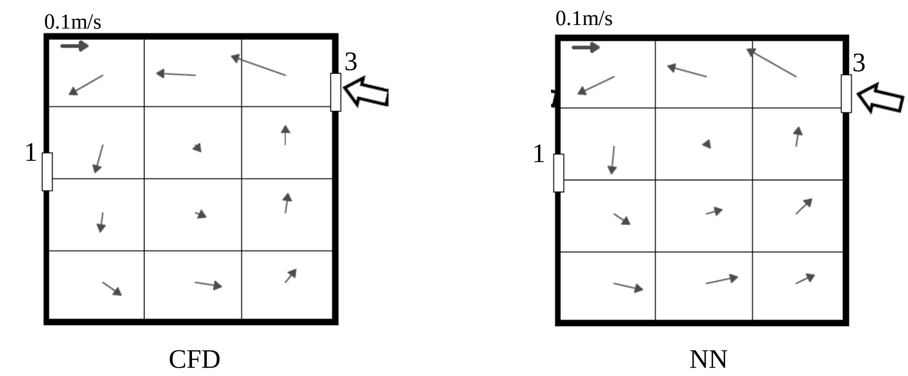


Figure 14. Wind velocity vectors distribution at 157.5 degree of Case 2

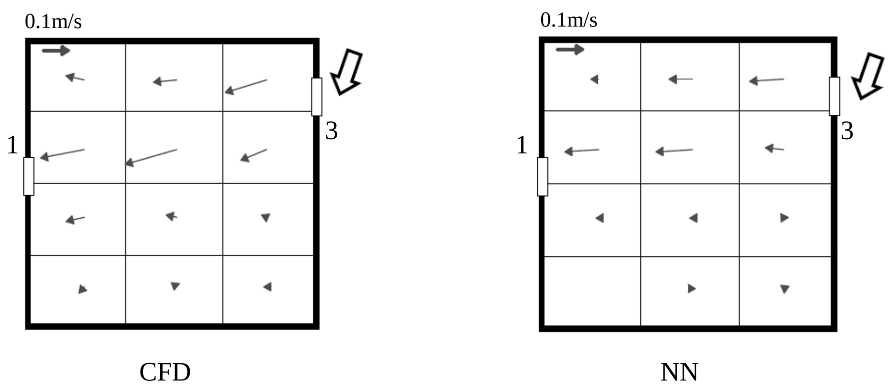


Figure 15. Wind velocity vectors distribution at 247.5 degree of Case 2

The simulation accuracy extremely lowered, when NN first learned the case with little air volume and no clear airflow pathway inside of the room such as at 90 of the wind direction degrees. It was because the value of the wind velocity was calculated exceedingly small and influenced on the simulation (Fig. 16).

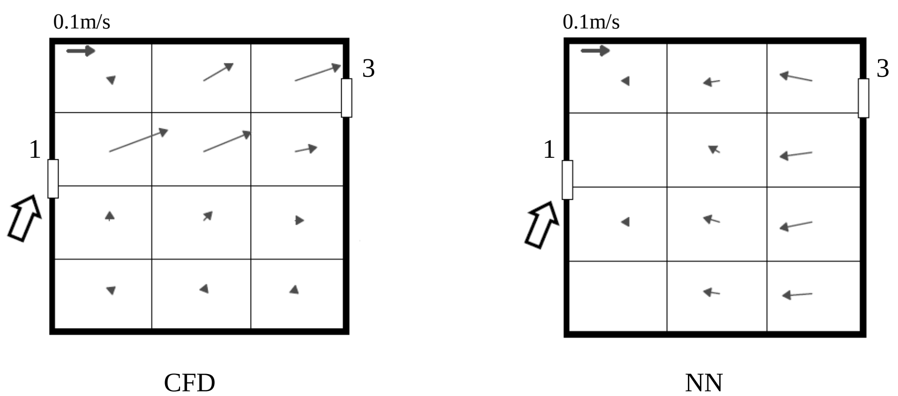


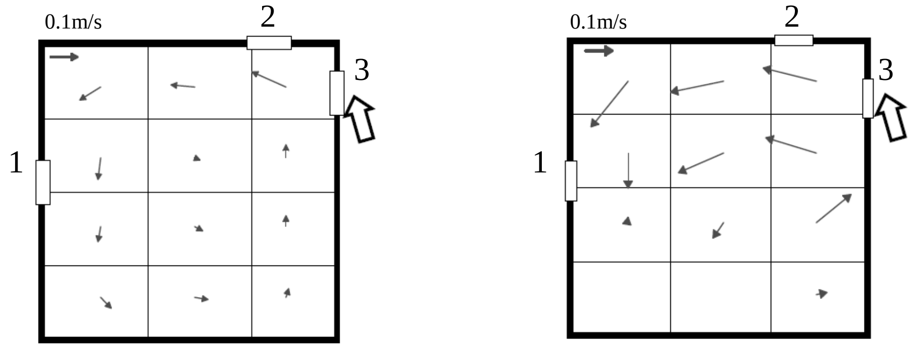
Figure 16. Wind velocity vectors distribution at 67.5 degree of Case 2

The velocity rates of NN were generally similar to those of CFD at any wind direction, and the simulation in Case 1 and 2 were highly accurate. Table 2 shows a comparison of the velocity rates in Case 2.

Degrees	22.5	67.5	112.5	157.5	202.5	247.5	292.5	337.5
CFD	0.14	0.11	0.04	0.07	0.10	0.11	0.12	0.12
NN	0.15	0.12	0.05	0.09	0.13	0.07	0.10	0.12

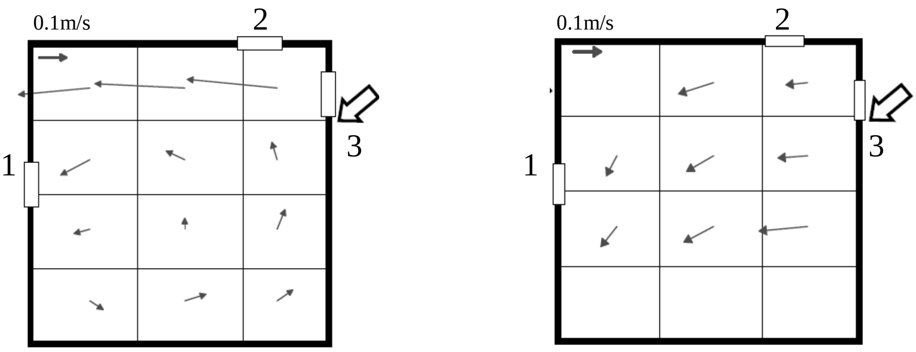
Table 2. Comparison of the velocity rates Case 2

So, the indoor airflow velocity distributions with all of the openings (1, 2, and 3) open were examined in Case 2, which had small calculation load and high simulation accuracy. As shown in Figure 17 and Figure 18, both of the conditions of the indoor airflow circulation were relatively similar to each other. But, there is still some problems remaining in the simulation accuracy in the small wind velocity areas.



CFD NN

Figure 17. Wind velocity vectors distribution at 112.5 degree of Case 2



CFD NN

Figure 18. Wind velocity vectors distribution at 202.5 degree of Case 2

CONCLUSION

This study dealt with the fundamental considerations about the cross-ventilated indoor air environmental simulations through NN. It revealed that the results of the simulations with NN tended similarly to the results of CFD under the condition that 2 openings were open in Case 1, Case 2 and Case 3.

By the combination of the cases with 2 openings open, the simulation of NN with 3 openings in Case 2, which had small calculation load and high simulation accuracy, gained low accuracy and basically resulted in similar wind directions to the results of CFD.

Further research is needed to examine other learning methods and to improve the calculation accuracy.

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