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1_C20

Examination of Occupant Arrangement in an Office Floor based on Nonuniformity of CO_2 Concentration Using Computational Fluid Dynamics (CFD) Simulation

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ABSTRACT

Heating, ventilating, and air conditioning (HVAC) systems attempt to achieve a uniform indoor environment. However, this can be challenging, because the placement and control of HVAC systems and sensors are affected by many unpredictable factors. The efficacious exploitation of this nonuniformity can lead to an improvement of indoor environment around occupants. Of the many indoor environment variables, we focused on the CO_2 concentration associated with ventilation. In the first part of this two-part study, computational fluid dynamics (CFD) was utilized to determine the CO_2 concentration distribution in an office space. First, we investigated the effects of the recommended ventilation improvement countermeasures including (a) increasing ventilation volume, (b) placement of air circulators (fans), and (c) restricting the number of occupants with staggered seating. Measure (a) contributed to expanding a well-ventilated area, whereas measure (b) resulted in the leveling of the CO_2 concentration distribution; in the case of (c), most occupants stayed in the well-ventilated area. Based on these results, we increased the number of occupants by relocating air circulators, desks, and occupants, and 72 occupants could stay in well-ventilated areas. The target space capacity calculated from the design standard was 75. In the second part, we attempted to predict the CO_2 concentration around occupants using neural network. The dataset of seating arrangement, sensor CO_2 concentration, and CO_2 concentration of each seat were created using CFD simulation. In this study, the CO_2 concentration of each seat was calculated with a root mean square error of less than 10 ppm. In future studies, it may be possible to increase the number of occupants in a well-ventilated area by considering the nonuniformity, and the use of neural network should be tested with real world data as input.

1 INTRODUCTION

The indoor environment is unsteady and nonuniform, because it is affected by many external factors and diverse occupant behavior (Zhou et al. 2017). Moreover, human thermal comfort differs individually(Wang et al. 2018). The ISO standard 7730:2005 recommends controlling the indoor environment to a predicted mean vote (PMV) in the range of –0.5 to 0.5 (Sawada 2014). As such, PMV-based control strategies have been realized in recent years (Tomoyuki. 2006) However, PMV is not without limitations; for example, it does not consider differences in race and gender and immediate past behavior (Zhou et al. 2017). Thus, using PMV may inadvertently favor the thermal comfort preferences of only select individuals . Recently, the development of internet of things (IoT) devices has paved the way for gathering increasingly detailed information about indoor

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environment and personal health (Nishino et al. 2017; Nishino et al. 2018). This information can help us understand the nonuniformity of the indoor environment, based on which optimal locations for individual can be suggested.

In the first half of this study (Section 2), we investigate the change in the number of occupants provided with good air quality after installing a circulator and changing the occupant arrangement considering the nonuniformity of CO_2 concentration in an office room. This is carried out by analyzing the distribution of CO_2 concentration in the office space using computational fluid dynamics (CFD). When optimizing the seating, it is important to determine the CO_2 concentration distribution in the room instantly to adjust the immediate preceding conditions to determine the new position of the occupants. However, CFD analysis need too many inputs and a long calculation time. Thus, in the latter half of this study (Section 3), we consider using neural network to determine the distribution of CO_2.

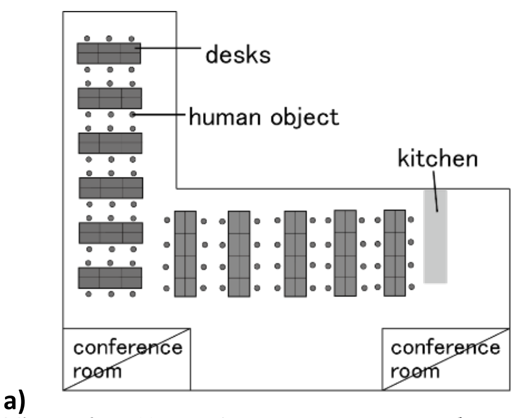
2 CHANGE IN OCCUPANTS UNDER GOOD AIR QUALITY WITH SEATING OPTIMIZATION

In this section, seating optimization is performed in two phases. In phase 1, the effects of three popular countermeasures recommended for ventilation are investigated. Then, in phase 2, using the results of phase1, optimization on the placement of desks, fans, and occupants is conducted, and the CO_2 concentration around the occupant is evaluated.

2.1 Method

Outline of target space. The shape of the target space is illustrated in Figure 1 (a). The 374 m^2 space is used as an office. For this study, the furniture arrangement shown in Figure1 (b) was adopted to accommodate the occupant in the entire room. The conference rooms on the lower left and lower right were not considered because they had separate air-conditioning systems.

As shown in Figure 1 (b), the air-conditioning system consists of six total heat exchangers and eight cassette-type air-conditioning units. The direction of the air stream from the total heat exchangers is denoted by arrows in Figure1 (b).



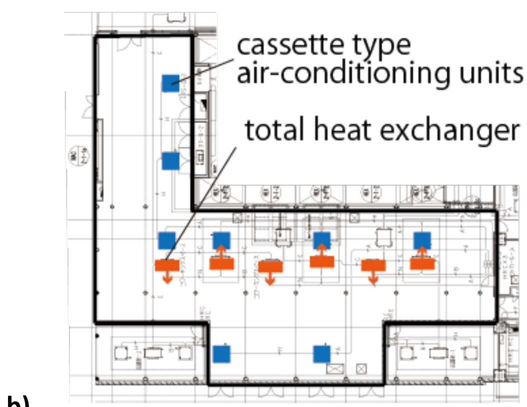


Figure 1 (a) Furniture arrangement used as an initial condition in Chapter 2, and (b) Air conditioning equipment arrangement and the plan of the target space

Overview of CFD analysis conditions. The CFD simulation was performed using FlowDesigner2020 (Advanced Knowledge Laboratory Inc.) software. The simulation settings are listed in Table1. A transient analysis was conducted. The time step for the unsteady analysis was set to 60 s . The temperature was analyzed under isothermal conditions at 25 °C.

The inflow and outflow boundary conditions are listed in Table1. The total heat exchanger was simulated by creating 1334 × 80 (mm) air outlets (inflow) and inlet (outflow) placed on the 1334 × 770 × 440 (mm) rectangular-shaped model. Isothermal conditions were assumed in this study. Heat exchange inside the total heat exchanger of the lossnai type and local airflow caused by the difference in temperature between the blowing air and indoor air near the outlet, were not considered. For the cassette type air conditioner, the specifications of a standard part (FXYFP112MC, Company A) obtained from the Air-Conditioning Society of Japan (http://www.akl.co.jp/support/parts/) were used. This type of air conditioner inhales indoor air, chills or warms it and exhales the chilled or warmed air. It does not contain fresh air introduction function which is covered by total heat exchanger.

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Table 1. Settings of CFD Simulation

Software	FlowDesigner2020	Numerical solution scheme	SIMPLEC, 1st-order
Analysis object	Wind speed, temperature, CO_2 concentration	Number of mesh elements	≈ 3,500,000
Turbulance model	High Reynolds number k-ε	Analysis area	29.917 × 25.221 × 2.900 m
Wall function	Logarithmic universal law + Spalding law	Time step	60 s
Total heat exchanger	Outlet(inflow)	Blow air volume(inflow)	6.95 m^3/min (8.33 m^3/min, in increased case)
		Size	1334 mm * 80 mm
		CO_2 concentration	400 ppm
	Inlet(outflow)	Inhale air volume(outflow)	6.95 m^3/min (8.33 m^3/min,in increased case)
		Size	1334 mm * 80 mm
Cassette-type air conditioner	Outlet(inflow)	Blow air volume(inflow)	6.5m^3/min (attached in 4 direction)
		Size	400 mm * 40 mm
	Inlet(outflow)	Inhale air volume(outflow)	26m^3/min
		Size	500 mm * 500 mm
Human object	CO_2 generated	23.6g/h	
	Size	200mm * 200 mm * 900 mm	
	Placement	z = 400mm	

Analysis procedure. The initial condition was decided according to the design standard, 0.2occupants/m^2. The floor area of the target space was 374m^2, thus, the number of occupants was set at 75. However, the number of desks in the office was set to 76 for convenience of arrangement. The outdoor CO_2 concentration and initial indoor CO_2 concentration were set to 400 ppm. The amount of CO_2 generated per person was set 23.6g/h. Assumming that the amount of CO_2 generated per person is 20L/h, the amount generated by 75 occupants is 1,500 L/h. Using the Seidel equation, the required ventilation volume was determined to be 2,500 m^3, and the ventilation volume of one total heat exchanger was set to 417m^3.

Figure 2 illustrates the procedure adopted. In phase1, through case(a) to case(f), the effectiveness of three countermeasures for ventilation was evaluated. The countermeasures are: increasing the ventilation volume, installing air circulators, and maintaining social distance by sitting in every other seat. In phase 2, through case (f) to case (k) and using the results from phase1, ways to increase the number of occupants staying in clean air were explored. Additional desks were put in unused areas, and also additional air circulators were put. Then, additional seating was conducted to the seat where CO_2 concentration is under 750 ppm. We used 750 ppm as the limit for additional seating.

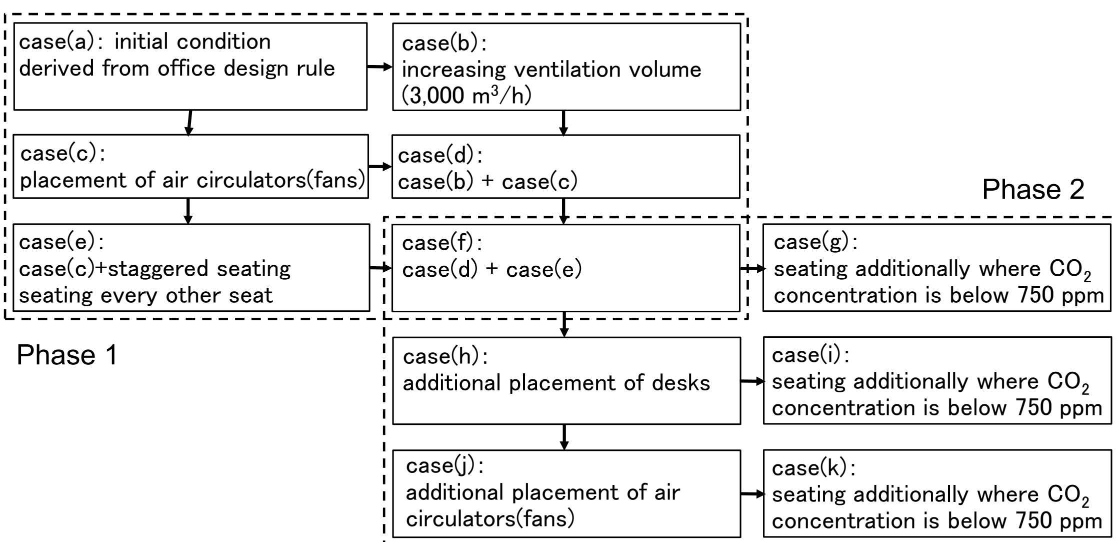

Figure 2 Procedure of the CFD analysis performed in two phases: phase 1 consists of case (a) to case (f), and phase 2 consists of case (f) to case (k)

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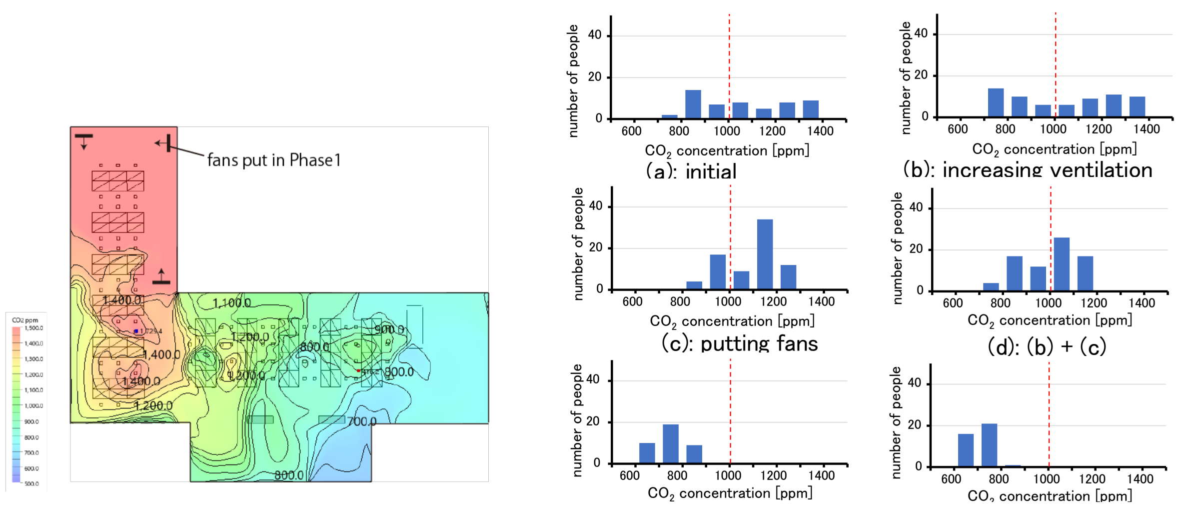
Indicators to be used. In this study, CFD analyses of the CO_2 concentration were performed to determine the ventilation nonuniformity. The ventilation standard used in building design is considered to be sufficient as a measure against the spread of the virus through droplet nuclei. In "Act on Maintenance of Sanitation in Buildings", the CO_2 level is stipulated to be no more than 1000 ppm. Our goal in this study is to maximize the area with CO_2 concentration below 1000 ppm, and if possible, make as wide area as possible below 800 ppm in order to think on the safe side considering that the standards for coronavirus prevention is yet to be clearly established, and that there is a possibility of the standard changing. Also, as the people themselves emit CO2, the CO2 concentration around occupants go up locally. Thus, we decide using 750 ppm, whick is lower than 800 ppm, for the limit of additional seating. A rectangle-shaped generating area named "human object"represents one human generating 23.6 g/h of CO_2. Additionally, a 200 × 200 × 200 mm rectangule-shaped object, named "sensor object", is created above the human object at z = 1500. The average CO_2 concentration of each mesh on the object surface was regarded as the CO_2 concentration for the corresponding seat.

2.2 Results

Results of PHASE1. Figure 3 (a) shows the analysis results for case(a). The data at z = 1,500 (mm) after 6 hours from the start was adopted. The resulting CO_2 concentration ranged between 700 and 1500 ppm and showed spatial nonuniformity. As seen in Figure 3 (a), the CO_2 concentration in the upper left area is high, because lossnai type total heat exchanger is not installed in this area. Therefore, in cases (c), (d), (e), and (f) of phase 1, fans were placed in this area. Figure 3 (b) shows the number of occupants in each CO_2 concentration zone based on the values of the sensor objects. From cases (a) and (b), increasing the ventilation volume increases the number of occupants exposed to CO_2 levels below 1000 ppm. However, the number of occupants staying in areas with poor ventilation (above 1200 ppm) did not change. The introduction of outside air appears to be effective in improving the ventilation in the room as a whole, but the areas with poor ventilation did not show improvement. From cases (a) and (c), by installing air circulators, the number of occupants stay in areas with 1300-1400 ppm and 700-800 ppm CO_2 level are both decreased. The air quality of the entire room was leveled. In cases (e) and (f), which included staggered seating, all occupants could stay in areas with CO_2 level below 1000 ppm. From case (d), combining the two countermeasures—increasing the ventilation volume and installing air circulators— is more effective than a single countermeasure independently. Moreover, case (f) shows that combining the three countermeasures improved the air quality around occupants more than implementing any one or two of them.



a) b)

Figure 3 (a) Initial CO_2 concentration distribution of case(a), and (b) Analysis of the number of occupants in the room for each CO_2 concentration zone in phase1

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Results of PHASE2. In phase2, the rearrangement of occupants, fans, and desks was studied based on the results of case(f) (Figure 4 (a)), so that more occupants could stay in the areas with CO_2 levels below 1000 ppm. The result of case(f) shows that at the bottom of the figure where no desks are placed, the concentration of CO_2 is low. In case(h), the desks were placed in this area, and seating was straggered. In addition, as the concentration of CO_2 in the area around the doorway on the right side of the figure is low, placing fans in this area is considered to increase the cleanliness of the air around the office desks, where occupants are expected to stay for a long time. In cases (g), (i), and (k), occupants seated additionally where the CO_2 concentration is 750 ppm or lower in cases (f), (h), and (j), respectively, to determine the maximum occupancy while keeping the CO_2 concentration in the areas below 1000 ppm. The reasons for setting 750 ppm as a criterion for determining allowable additional occupants was not only because the value is significantly below the target value of 1000 ppm but also to ensure the rise in the ambient CO_2 concentration due to additional occupants does not affect those placed in ideal ventilation (< 800 ppm) areas . As shown in Figure 5, most occupants—all but one—were seated in areas below 1000 ppm in case (k).

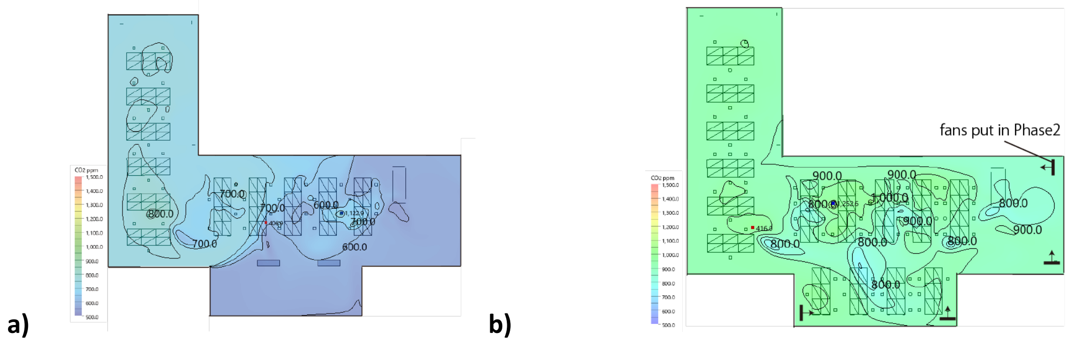

Figure 4 (a) CO_2 concentration distribution in initial case of phase2, case(f), and (b) CO_2 concentration distribution in last state, case(k)

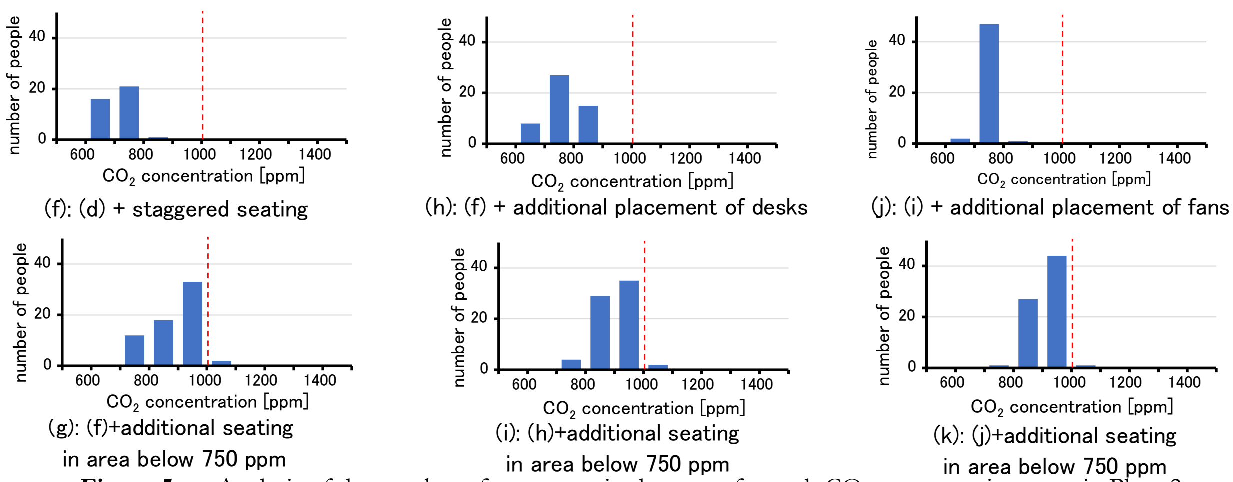

Figure 5 Analysis of the number of occupants in the room for each CO_2 concentration zone in Phase2

Results of PHASE1 and PHASE2. Table 2 shows the total number of occupants in the room and those staying in the areas with CO_2 level below 1000 ppm in each case. In Phase2, more occupants could stay in the areas with CO_2 level below 1000 ppm than in case(f). In the final case (case(k)), 72 occupants could stay in the area with concentration below 1000ppm, which is close to the occupancy of 75, calculated from design standards. Furthermore, in the entire target space, the area with CO_2 level above 1000 ppm became smaller in case (k) shown in Figure 4(b) than in case (a) shown in Figure 3(a).

Table 2. Overall number of occupants and in areas below 1000 ppm in each case

case	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
Overall number of occupants	76	76	76	76	38	38	65	50	70	50	73
Staying below 1000 ppm	23	30	21	33	38	38	62	50	68	50	72

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3 ESTIMATION OF CO_2 CONCENTRATION DISTRIBUTION USING NEURAL NETWORK

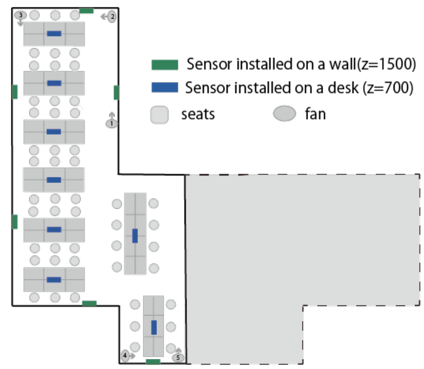
To realize air-conditioning using nonuniformity as in Section 2, it is important to predict values at every point in a room from limited values measured with IoT sensors, which is called Soft Sensing. This section details a rudimentary study done to assess the possibility of using neural networks in the prediction of Soft Sensing

3.1 Methods

The explanatory and objective variables set in this study are listed in Figure 6(a). The data used were those extracted from the CFD analysis pertaining to the left half of the target space (Figure 6(b)) used in Section 2.

	Kind of data	The number of data
Explanatory variables	sensor object value	14
	seating situation	50
Objective variable	each seat value	50

a)



b)

Figure 6 (a) Explanatory and objective variables, and (b) target space considered in section 3, which is the left half of the target space studied in section 2

Datasets Creation. The maximum number of occupants in the room was 50, and an increased ventilation rate of 8.33 m^3/min was used. The size of the analysis area was set to 12800 × 25220.8 × 2900 mm, and the number of mesh elements was set to 923,210 to fit the size of the target space. Other settings of the CFD simulation are the same as those in Table 1. The occupant seating arrangement can have many patterns. In order to avoid bias in data, the number of seating patterns for CFD analysis was set according to Table 3. For each occupant number band, the seating arrangements were decided at random with using Python up to the number of patterns shown in Table 3.

Table 3. Number of seating patterns for CFD analysis for each occupant number band

number of occupants	1	5	10	20	25	30	35	40	45	50
number of patterns	15	10	10	10	15	10	10	10	15	1

Transient analysis was conducted for the 106 patterns shown in Table 3 over a span of 1.5 h. The 1 min interval data from 1 to 1.5 h was used so that the CFD analysis of each pattern produced 31 different data points. Overall, 3286 pattern datasets (31 data points × 106 patterns) were obtained. A total of 822 patterns were used as test data, and 2464 patterns were used as training data. As we chose the transient simulation and used the dataset between 1 to 1.5 h, multiple similar but different objective variables can be collected for a single explanatory variable. This works in a similar way to creating noise-loaded data for image analysis. In addition, for an actual room, there can be multiple steady states mixed together because other movements occur between the time of formation of one state and the time when steady state is reached.

Layer Commposition. The optimal layer structure for the created dataset was investigated. The variables in this study are the number of nodes, number of layers, and learning rate(lr). For the number of nodes, two commonly used combinations of 64 and 128, and 128 and 256 were tested. For the number of layers, the cases of 4 and 6 layers were tested. The learning rate was started at 0.01 and was gradually increased. Considering the computation time and the probability of overlearning, the 12 patterns shown in Figure 7 were examined.

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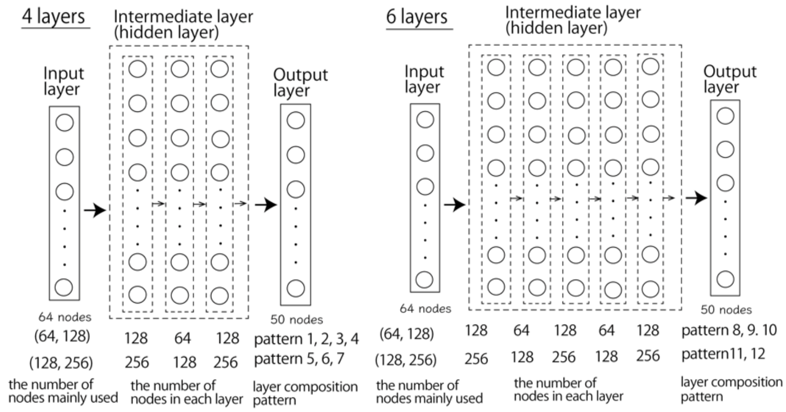
Table 4. Layer structures and learning ratea tested

layer pattern	the number of nodes	the number of layers	learning rate
1	64,128	4	10^-2
2	64, 128	4	10^-3
3	64, 128	4	10^-4
4	64, 128	4	10^-5
5	128, 256	4	10^-2
6	128, 256	4	10^-3
7	128, 256	4	10^-4
8	64, 128	6	10^-2
9	64, 128	6	10^-3
10	64, 128	6	10^-4
11	128, 256	6	10^-3
12	128, 256	6	10^-4

a)



b)

Figure 7 (a) Layer structures and learning rate tested, and (b) Overview of the layer structure

Method for determining the layer structure and learning rate. To investigate the optimal layer composition and learning rate for the dataset, root mean squared error (RMSE) was used. In addition, the mean absolute error (MAE) was calculated to increase certainty. The data were normalized, but the RMSE and MAE were calculated in decoded form.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \widehat{yi})^2} \qquad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(yi - \widehat{yi}) \qquad (2)$$

*Where n is the number of objects, **yi** is the value, $\widehat{\mathbf{yi}}$ is average value.*

3.2 Results

Table 5 presents the results of the analyses on 12 layer structures. The analyses were conducted using the dataset as described in Section 3.1. Both the RMSE and MAE values were minimum for Pattern 12. For Patterns 1 to 4, the learning rate was changed from 0.01 to 0.00001. As the learning rate increased, the RMSE and MAE values decreased; however, pattern 4, when the learning rate is set 0.00001, showed increased values of RMSE and MAE. Conversely, for patterns5, 6, and 7, the RMSE and MAE values decreased as the learning rate increased. For pattern 5, overlearning seems to be occurring. In addition, overlearning occurred in pattern 8 with a learning rate of 0.01. RMSE and MAE decreased in Pattern 9 with a learning rate of 0.001, and increased in Pattern 10 with a learning rate of 0.001.

Among the patterns 2, 6, 9, and 11 with lr = 0.001, the minimum error was found for pattern 2, and among the patterns 3, 7, 10, and 12 with lr = 0.0001, it was found for pattern 12. Figure 8 shows the plots of the objective variables of the test data (original) and the predictions obtained with the explanatory variables of the test data as inputs to the model (prediction). The prediction accuracy of pattern 12 was better than that of pattern 1.

Table 5. RMSE and MAE for each layer structure

Pattern	1	2	3	4	5	6	7	8	9	10	11	12
RMSE	31.36	10.37	9.27	19.31	284.5	11.49	9.01	288.97	10.75	10.98	14.79	6.99
MAE	20.68	7.39	5.70	12.80	242.7	7.71	6.40	242.47	7.64	6.92	10.85	4.74

Table 6 presents the RMSE for each occupants number band listed in Table 3. The RMSE is the largest when the number of occupants is 35 and smallest when the number of occupants is 5. Figure 8 shows the difference between prediction with neural network and the real data for 50 seats.

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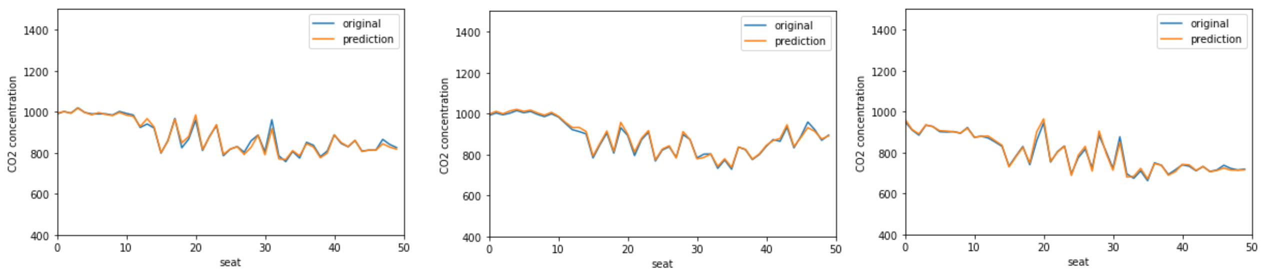
Table 6. RMSE for each occupant number band

number of occupants	1	5	10	20	25	30	35	40	45	50
RMSE	6.86	6.06	7.18	8.54	7.72	9.11	10.08	6.09	7.96	8.73



a) b) c)

Figure 8 Objective variable of the test data (original) and prediction data obtained with the explanatory variables of the test data as inputs to the model (prediction) for (a) 1 person, (b) 35 people, and (c) 50 people staying in the room.

4. CONCLUSION

In this two-part study, constructive use of the nonuniformity of ventilation in an office space, and the possibility of using neural networks to predict ventilation nonuniformity in a room are investigated.

In phase1 of the first part of the study, we checked the degree of influence on air quality around occupants of the three countermeasures recommended in improving the air quality (increasing ventilation volume, placement of air circulators, and seating every other seat). Increasing ventilation volume improves the air quality where air quality has always been good. The placement of air circulators leveled the air quality of the whole room. Restricting the number of occupants with staggered seating improved the air quality of the whole room. The combination of these countermeasures was more effective than any of the individual countermeasures. In phase2, ways to increase the area and occupant with good air quality were determined. It is possible for the number of occupants staying in the area below 1000 ppm to be almost the same as that determined based on the design standard, by devising the arrangement of desks, putting additional air circulators, and increasing the amount of ventilation, considering the ventilation nonuniformity in the room.

In the second part, as a first step in developing a method for the instantaneous identification of nonuniformity in a room, an elementary study for predicting the CO_2 concentration around each occupant using neural network was conducted. It was found that a neural network with an appropriate layer structure and data set has the potential to predict the CO_2 concentration for each occupant based on the seating plan and limited sensor data. As this study is an imitation of the real room, and the data set is made from limited patterns, there is a bias in each occupancy pattern.

The actual ventilation conditions are influenced by several factors. The factors that were not considered in this study include the thermal environment and gravitational settling of diffuse materials, and a more detailed study considering these factors is required. In addition, air quality is a dynamic factor, that is affected by the movement of occupants and the status of openings at any given time. It may be possible to correlate the nonuniformity of environmental factors of the room and the acceptable number of occupants if we can determine the air quality of each place using sensors and simulation analysis. Here, the use of neural network can be effective in predicting the air quality of each location.

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