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MULTI-CRITERIA OPTIMAL DESIGN OF RESIDENTIAL VENTILATION SYSTEMS

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ABSTRACT

This paper addresses the optimal design of residential ventilation systems in an apartment floor plan in Korea. The term "optimal design" refers to the selection of a ventilation method (mechanical, hybrid), type of heat recovery (total, sensible only), outdoor airflow rate, and the optimal sizing and location of supply diffusers/exhaust registers. Decision-making criteria include initial and operation costs, indoor air quality, energy use, and comfort. To solve this multi-criteria optimal design problem, we introduce multi-objective optimization using a genetic algorithm and Pareto optimality. The Genetic Algorithm (GA) was chosen to solve the constrained discontinuous optimization problem. The software CONTAMW 2.4 developed by NIST (National Institute of Science and Technology) was used to simulate ventilation phenomena. The problem was then solved by integrating GA, Pareto optimality, and CONTAMW simulation runs. The paper presents an example of an optimal design problem for a specific apartment plan.

INTRODUCTION

With increased expectation of better indoor environment, much research has focused on Indoor Air Quality (IAQ). IAQ is determined by thermal control, removal of indoor contaminants, proper ventilation, occupant's behavior, etc. The determination of an adequate ventilation method (natural, hybrid, or mechanical), type of heat recovery, size and location of diffusers and registers, and the outdoor airflow rate is crucial. A new ventilation code (KMOCT, 2006) was enacted in Korea in 2006 to ensure a healthy environment for occupants. The code specifies a minimum of 0.7 Air Changes per Hour (ACH, h^{-1}) in multi-family apartment buildings.

This study aims to approach the design of residential ventilation systems in multi-family apartment buildings from the architectural perspective. A distinction should be made between the mechanical and architectural perspectives. Optimal design in light of the mechanical perspective focuses on the efficiency of heat recovery, fan configuration, filter type and location, and motor efficiency. Optimal design in light of the architectural perspective focuses on the ventilation method, size and location of diffusers and grilles, the outdoor airflow rate, and heat recovery method.

Most optimal design problems involve multiple criteria, in this case, the initial costs, operation costs, comfort, and indoor air quality. In general, the multi-criteria decision making (MCDM) process has two elements (Wright et al, 2002):

(1) the designer must make a *decision* as to which compromise between the criteria results in the most desirable design solution;
(2) a procedure to *search* for one or more solution s that reflect the desired pay-off between crite-ria

The relationship between decision and search has three forms (Wright et al, 2002; Van Veldhuizen et al, 2000; Miettinen, 2001)

- *Approach I*: *A priori* preference articulation (decide → search), in which the decision maker (DM) defines the preferred pay-off between the criteria in advance of the search (for instance, the designer may say that the capital cost of the building is twice as important as the operating cost). The most common *a priori* approach is that in which the DM assigns weights to each criteria, the weighted sum of the criteria then forms a single objective function.
- *Approach II*: *Progressive* preference articulation (decide ↔ search), in which the decision and search are intertwined, with the DM using progressive solutions to inform the decision making process and the final choice of pay-off. This approach is likely to be computationally intensive and time-consuming since a new solution would require a repeated optimization and simulation.
- *Approach III*: *A posteriori* preference articulation (search → decide), in which the DM is presented with a set of solutions and then chooses a final design solution from that set. This approach does not use the determination of weights over different criteria, and imitates decision making in the real world. In general, decision making involves non-compatible criteria such as initial costs vs. operation costs vs. comfort vs. air quality. Most decisions are made not based on the weighted sum of different criteria, but based on the intuitive or

rational judgment of the DM. For instance, it is rare that a buyer purchases a computer, a car, or clothes based on the weighted sums of price, design, color, performance, and reputation. Usually, the buyer makes a decision using a set of solutions according to his/her intuitive or rational judgment. Approach III provides a set of optimal solutions from which a DM can make a choice.

In this study, (1) initial costs ($), (2) operation costs ($), (3) Percentage Dissatisfied (PD), and (4) CO_2 concentration (ppm) were selected as elements in the objective function. Architectural parameters such as (1) the ventilation method, (2) location of supply diffusers, (3) the outdoor airflow rate, and (4) the heat recovery method are chosen as design variables. The objective function consisting of the aforementioned design variables is discontinuous and nonlinear which leads to difficulty in using a classical optimization method (the gradient-based search method) to find an optimal solution that minimizes the objective function. Accordingly, the Genetic Algorithm (GA) was chosen since it is applicable to our optimization problem. For the multi-criteria decision making, the "a posteriori articulation (search → decide) approach" was employed using Pareto optimality.

MULTI-CRITERIA OPTIMIZATION

Genetic Algorithm (GA)

Genetic algorithms that were developed by Holland (1975) constitute a class of search, adaptation, and optimization techniques based on the principles of natural evolution. Schaffer (1985) suggested that the GA can be effectively used in solving multi-criteria optimization problems. While the GA is effective in finding the global minima, it is more computationally intensive than the gradient-based method (Table 1). The GA was selected in this study since it can efficiently solve for nonlinear and nondifferentiable optimization problems.

Table 1
Gradient-based method vs. the Genetic Algorithm (Thitisawat, 2004)

	Gradient-based method	**Genetic Algorithm**
Limitation to solve non-differentiable problems	Yes	No
Becoming trapped at a local minima	Yes	No
Computationally expensive	No	Yes
Problem of an initial solution selection	Yes	No

Pareto Optimality

To find an optimal solution for multi-criteria problems, an approach must first be determined. As explained earlier, the *a priori* preference articulation (decide→search) approach (Approach I) involves the DM first determining the weights and then finding an optimal solution. Methods for determining weights include the WSM (Weighted Sum Model) (Fishburn, 1967), WPM (Weight Product Model) (Miller and Starr, 1969), AHP (Analytic Hierarchy Process) (Saaty, 1980), ELECTRE (Elimination and Choice Translating Reality) (Benayoun et al, 1966) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) (Triantaphyllou and Mann, 1989). These methods find an optimal solution that minimizes the objective function ($F(x)$) by applying weights to Eq. (1).

$$\min\ F(x) = w_1 \times f_1 + w_2 \times f_2 + \cdots\cdots w_n \times f_n \qquad (1)$$

where, w_i = weights and f_i = objective function elements.

The weights in Eq. (1) are usually determined based on the DM's subjective and qualitative judgment. Even if the weights are determined though a comprehensive and rational framework, such weights are not an absolute solution for multiple non-comparable criteria. For example, the weights of apples, bananas, oranges, and watermelons would vary according to personal preference and thus no absolute weights exist. Approach II requires repeated search and optimization by changing the weights until a satisfactory solution is found, thus resulting in greater computation time. In this study, the "a posteriori articulation (search→decide) approach" (Approach III) was used. This approach generates a Pareto optimal set (non-dominated solutions) which allows the DM to choose his/her preferred solution from the set.

The concept of Pareto optimality is shown in Fig. 1. A superior solution is referred to as a non-dominated Pareto, and a non-superior solution as a dominated Pareto. A non-dominated Pareto solution is always superior to any dominated Pareto solution. In Fig. 1, A, B, and C are always superior to A1, B1, and C1, and superiority among A, B, and C cannot be determined. A, B, and C are not dominated by any other solution, and a set of such non-dominated Pareto solutions is referred to as a "Pareto optimal set" or "efficient frontier". This study aims to find a Pareto optimal set using the multi-criteria optimization.

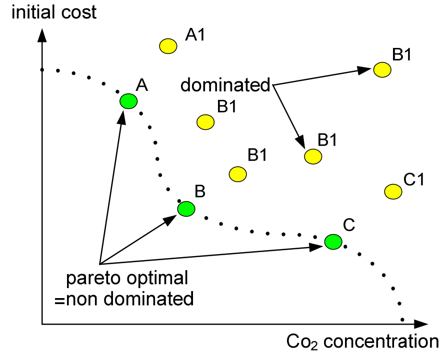


Figure 1 Pareto Optimality

Integration of the GA, Pareto optimality with CONTAMW 2.4

Fig. 2 shows the procedure for generating a Pareto optimal set by integrating the Genetic Algorithm and Pareto optimality with CONTAMW 2.4 ventilation simulation runs. The generation is an iterative process using initial population, fitness sharing, selection, recombination/crossover, and mutation towards the efficient frontier.

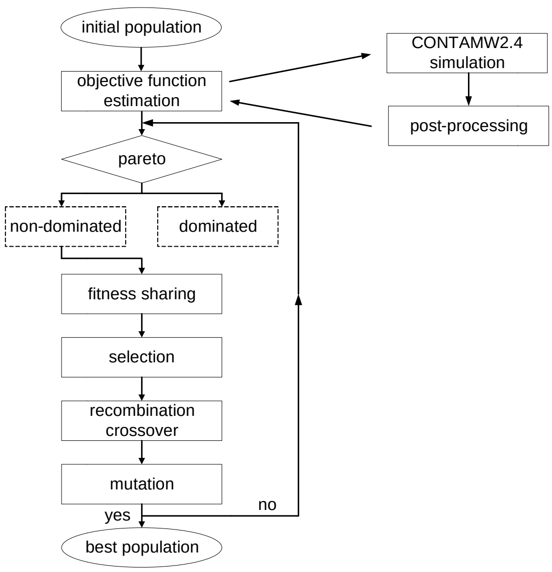


Figure 2 Integration of the GA, Pareto optimality with CONTAMW 2.4 simulation

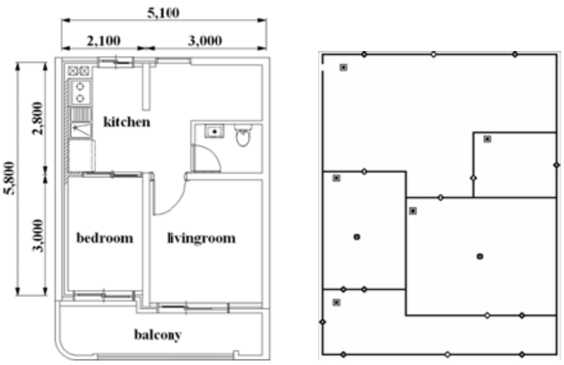
APPLICATION

Building description and simulation

An apartment building located in Jeju, Korea was selected for this study. The floor plan is shown in Fig. 3(a). Through site visits and questionnaires, it was found that the average number of occupants was two per household, and that the occupants spend most of their time in the living room and bedroom.

To simulate the airflow rate entering the building, CONTAMW 2.4 developed by the National Institute of Standards and Technology (Walton, 2005) was selected. The reasoning is as follows: if a computationally intensive approach (e.g. Computational Fluid Dynamics, CFD) is selected for the large number of simulation runs required for the GA optimization, this will become a hindrance. CONTAMW 2.4 is not the most detailed approach compared to CFD, but accurate enough and well-suited for assessing ventilation phenomena in a building. CONTAMW, based on nodal flow network modeling, predicts the time histories of the airflows between nodes and the concentrations of indoor pollutants. Fig. 3(b) shows the COMTAMW 2.4 model. The simulation inputs were obtained from site visits and construction documents. The simulation was performed on winter days since most residents fully utilize natural ventilation by opening doors and windows during the intermediate and summer seasons. During simulation runs, it was assumed that windows and doors were closed (except doors to the living room and bedroom) while the ventilation system was operating.

Be noted that the uncertain analysis was not included in the study since the use of the uncertainty analysis would become a bottleneck for GA. Thus, the base values of input variables (Hyun et al, 2008) were selected in the study.



(a) *(b)*

Figure 3 Floor plan and CONTAMW Model

Design Variables and objective function

The ventilation method, size and location of diffusers, the outdoor airflow rate, and heat recovery method were selected as design variables. The initial investment cost, operation cost (fan energy, heating, and maintenance such as filter exchange and cleaning), Percentage Dissatisfied, and CO_2 concentration were chosen as elements of the objective function. Table 2 and Eq. (2) outline the design variables and objective function elements.

Table 2
Encoding Used

Encoding Used		Remarks
X_1	0	Hybrid supply not installed (living room)
	1	Hybrid supply installed (living room)
X_2	0	Hybrid supply not installed (bedroom)
	1	Hybrid supply installed (bedroom)
X_3	0	Hybrid supply not installed (dining room)
	1	Hybrid supply installed (dining room)
X_4	0/100/150 /200/250/350	Total heat exchanger’s airflow rate (CMH), 0 if not installed (living room)
X_5	0/100/150 /200/250/350	Total heat exchanger’s airflow rate (CMH), 0 if not installed (bedroom)
X_6	0/100/150 /200/250/350	Total heat exchanger’s airflow rate (CMH), 0 if not installed (dining room)
X_7	0/100/150 /200/250/350	Sensible heat exchanger’s airflow rate (CMH), 0 if not installed (living room)
X_8	0/100/150 /200/250/350	Sensible heat exchanger’s airflow rate (CMH), 0 if not installed (bedroom)
X_9	0/100/150 /200/250/350	Sensible heat exchanger’s airflow rate (CMH), 0 if not installed (dining room)
X_{10}	0/60/120 /180/240/300	Hybrid exhaust rate (CMH), 0 if not installed (dining room)

$$MINF(X)=F(f_1, f_2, f_3, f_4) \quad (2)$$

Where,

f_1= Initial Investment Cost (KRW)
f_2= Operation Cost (KRW / Yr)
f_3= Percentage Dissatisfied (%)
f_4= CO_2 Concentration (PPM)

Optimization process

The optimization process consists of the following four steps:

- *Step 1: encoding and population size*

Step 1 involves defining the encoding used for the design variables as shown in Table 2. X1-X3 are 1 if a hybrid supply is installed, and 0 otherwise. X4-X6 and X7-X9 are the airflow rates of the total and sensible heat exchangers (CMH: Cubic Meters per Hour), and 0 indicates that a heat exchanger is not installed. X10 is the rate of the hybrid exhaust (CMH). X1-X10 are randomly selected within the range of the boundary conditions and then converted into a 2000:1 vector. In other words, each of X1-X10 consists of 2000 individuals. For this study, the size of the subpopulation was set at 40, and the individuals in the subpopulation were set at 50 to generate the initial population, resulting in 2000.

It is important to establish a proper population size for an optimization problem (Reed et al, 2001). The size in this study was obtained through seven cycles of “trial and error”.

- *Step 2: CONTAMW 2.4 and GA*

Step 2 involves integration of CONTAMW 2.4 with GA on the MATLAB platform. The process is as follows: (1) The CONTAMW simulation input files are read into MATLAB, (2) a new individual generated by the GA is overwritten into the CONTAMW 2.4 simulation input file by MATLAB m-codes, and (3) CONTAMW 2.4 is executed from MATLAB. Once a CONTAMW 2.4 simulation result file is created, the file is converted to a text file to be read in MATLAB. It should be noted that the CONTAMW 2.4 simulation result file is a binary file and SimRead3.exe (a command to convert a binary file to a text file) is automatically executed in MATLAB to convert it to a text file. The hourly CONTAMW simulation was conducted on Jan 1st. In Step 2, CONTAMW 2.4 input files are created from MATLAB, CONTAMW 2.4 simulation runs are carried out, and the results are read until the iterative process finds a global minima.

- *Step 3: calculation of objective function*

In Step 3, the four objective function elements (initial investment cost, operation cost, PD, and CO_2 concentration) are calculated. The initial investment cost data was provided by a ventilation company participating in this study. The operation cost included fan energy use, heating energy, and maintenance (filter exchange and cleaning). Fan and maintenance cost data were provided by the participating company. The heating energy calculation was based on the hourly weather data (winter months, Oct.-Feb.), and the method for calculating heating energy was based on NEN 2916 (1999).

The PD was calculated based on Fanger (1988). The CO_2 concentration was selected as a measure of IAQ since it is a typical contaminant generated primarily by occupants, and the measurement of CO_2 in occupied spaces has been widely used to evaluate the sufficiency of outdoor air supply in indoor spaces (ASHRAE, 2005). In the CO_2 calculation, an adult was assumed to generate 0.31 liters per minute (ASHRAE, 2004). We chose 1,000 ppm as the threshold of CO_2 concentration which is not a mandatory limit, but is a value recommended in the code (KMOCT, 2006). The number of occupants in each room (Fig. 3) was obtained through on-site interviews and questionnaires. The PD and CO_2 concentration were calculated every hour for 24 hours in each zone (living room, bedroom, and dining room). To reduce the computation time required by the Genetic Algorithm, PD (Fanger, 1988) was categorized into three levels (A, B, and C), and CO_2 concentration was rounded up to the nearest hundred PPM.

- *Step 4: finding Pareto set*

Step 4 involves finding the Pareto optimal solution set. The number of generations was set at 500. Theoretically, the maximum number of trial solutions can be 1,000,000 (500 multiplied by 2,000 individuals). The individuals in X_1-X_{10} generated in Step 1 made up a single generation in Steps 2-4. When one generation finished, new individuals were generated in Step 4 by fitness sharing, selection, recombination/crossover, and mutation, after which the optimization process was repeated according to the number of generations. The NSGA-II method proposed in (Deb, 2000) was used so that diversity of individuals could be maintained without the DM having to determine the niche size.

RESULTS

Verification of the Optimal Solutions

Table 3 shows the results of the optimization algorithm that combines the Genetic Algorithm and Pareto optimality. A set of Pareto optimal solutions consisted of 18 solutions. It should be kept in mind that the 18 Pareto optimal solutions were always superior to the others in the option space. In other words, whenever an optimal solution was selected by the DM, no alternative existed which was superior to the selected one. To validate the results, three approaches were employed. The first was to check the Pareto optimal solutions using a three-dimensional graph (Figs. 4-5), the second was to cross-compare the dominance relationships among the 18 Pareto optimal solutions, and the third was to check the superiority of the optimal solutions by varying the design variables.

Table 3

Optimal Designs (Non-Dominated Pareto Solution Set)

Non-Dominated Solution														
Optimal Design	**Design Variables**										**Objective Functions**			
	Hybrid (supply diffuser)			Total Heat Exchanger (CMH)			Sensible Heat Exchanger (CMH)			Hybrid (CMH) (exhaust)	Initial investment (KRW)	Operation cost*** (KRW/Yr)	% Dissatisfied (PD)	CO_2 Concentration (PPM)
	LR (X_1)	BR (X_2)	DR (X_3)	LR (X_4)	BR (X_5)	DR (X_6)	LR (X_7)	BR (X_8)	DR (X_9)	DR (X_{10})				
1	0*	0	1**	0	0	0	0	0	0	60	710,000	151,230	17.6	1100
2	0	0	1	0	0	0	0	0	0	120	710,000	292,450	9.8	800
3	1	0	0	0	0	0	0	0	0	120	750,000	292,450	9.8	700
4	0	0	0	0	0	100	0	0	0	0	1,000,000	182,400	11.5	900
5	0	0	0	150	0	0	0	0	0	0	1,252,900	223,590	7.9	800
6	0	0	0	0	150	0	0	0	0	0	1,252,900	223,590	7.9	800
7	0	0	0	0	0	150	0	0	0	0	1,252,900	223,590	7.9	800
8	0	0	0	0	0	200	0	0	0	0	1,569,700	264,780	5.9	700
9	0	0	1	0	100	0	0	0	0	60	1,710,000	333,630	7.4	700
10	0	0	1	100	0	0	0	0	0	60	1,710,000	333,630	7.4	700
11	0	0	1	0	100	0	0	0	0	120	1,710,000	474,850	5.3	600
12	1	0	0	0	100	0	0	0	0	180	1,750,000	616,070	4.1	500
13	0	0	0	100	100	0	0	0	0	0	2,000,000	364,780	5.9	600
14	0	0	0	100	0	100	0	0	0	0	2,000,000	364,780	5.9	600
15	0	0	0	0	100	100	0	0	0	0	2,000,000	364,780	5.9	600
16	0	0	0	150	100	0	0	0	0	0	2,252,900	405,970	4.6	500
17	0	0	0	100	150	0	0	0	0	0	2,252,900	405,970	4.6	500
18	1	0	1	200	250	0	0	0	0	60	4,326,300	731,960	1.9	400

LR: Living Room, BR: Bed Room, DR: Dining Room

*diffuser not installed, **diffuser installed, ***includes fan energy, heating energy (Oct. – Feb.), maintenance

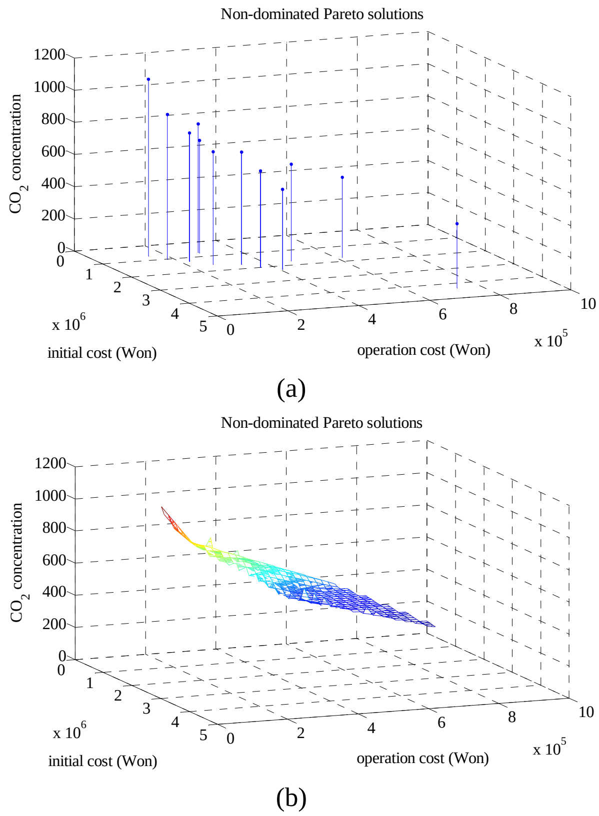


Figure 4 18 Pareto optimal solutions #1 (XYZ: investment cost, operation cost, CO_2 concentration)

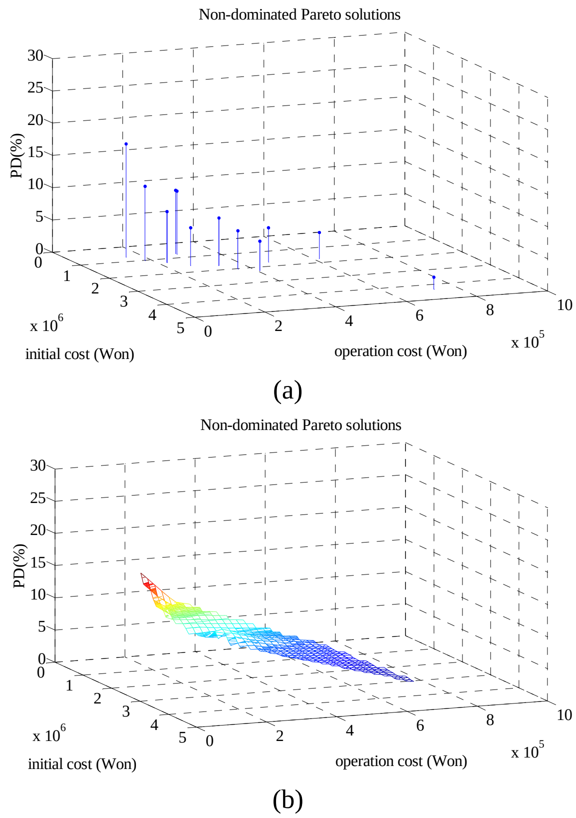


Figure 5 18 Pareto optimal solutions #2 (XYZ: investment cost, operation cost, PD)

The first method is advantageous since it allows for a visual check using a three-dimensional graph. The optimality of the 18 optimal solutions having four elements in the objective function (initial investment cost, operation cost, PD, CO_2 concentration) can be confirmed by plotting two 3-Dimensional graphs (Type #1: initial investment cost (X-axis), operation cost (Y-axis), CO_2 concentration (Z-axis), and Type #2: initial investment cost (X-axis), operation cost (Y-axis), PD (Z-axis)).

The 18 selected optimal solutions were the Pareto optimal set as shown in Figs. 4-5.

The second validation method is described below, but its entire details will not be given in this paper due to length. Comparisons between the optimal solutions were made to confirm that every optimal solution generated by the algorithm was a non-dominated Pareto solution.

- *Optimal Design #1 vs. #2 (Table 3)*: Design #1 had lower operation costs than #2, whereas Design #2 had a lower PD and CO_2 concentration than #1, indicating that both designs were non-dominated Pareto solutions whose superiority could not be determined.
- *Optimal Design #4 vs. #5 (Table 3):* Design #4 had a lower initial investment and operation costs than #5, whereas Design #5 had a lower PD and CO_2 concentration than #4, indicating that both designs were mutually non-dominated.
- *Optimal Design #17 vs. #18 (Table 3):* Design #17 had a lower initial investment and operation costs than #18, whereas Design #18 had a lower PD and CO_2 concentration than #17, indicating that both designs were mutually non-dominated Pareto solutions.

By cross-comparing all of the 18 optimal designs as explained above, it was found that all solutions shown in Table 3 were mutually non-dominated.

The third validation method validated the optimality of the Pareto optimal solutions by varying the values of the design variables (ventilation method, size and location of diffusers and grilles, outdoor airflow rate, heat recovery method).

- Change in supply diffuser location: The diffuser location in Design #1 in Table 3 (hybrid, supply diffuser located in the dining room) was changed to the living room and bedroom for the purpose of comparison. As shown in Table 4, Solution #1 became a non-dominated Pareto when the supply diffuser was located in the dining room. Installing the supply diffuser in the living room or the bedroom required a higher initial investment cost because an additional diffuser should be installed on the wall of the balcony (Fig. 3 (a)). Although the actual CO_2 concentration level can differ according to supply diffuser location, the CO_2 levels were identical for all three cases in Table 4. As described earlier, this is due to the fact that the CO_2 values were rounded up to the nearest hundred PPM for the sake of GA computation time. The calculation resolution can be adjusted by changing the degree of rounding, but for the purposes of this study, an accuracy level of CO_2 concentration on the order of less than 100 PPM is considered acceptable in ventilation simulations.

Table 4
Change of a supply diffuser location

Design	**Supply diffuser location**	**Initial Invest ment cost (KRW)**	**Opera tion cost (KRW /Yr)**	**PD**	**CO_2 (PPM)**
Non-dominated Solution (Design 1)	Dining Room	710, 000	151, 230	B	1100
Dominated Solution	Living Room	750, 000	151, 230	B	1100
Dominated Solution	Bed Room	750, 000	151, 230	B	1100

- Change in airflow rate: The capacity of the total heat exchanger in Design #4 (Table 3) was varied from 150 to 200, 250, and 350 CMH for comparison. As indicated in Table 5, the solutions become non-dominated Paretos for airflow rates of 100, 150, and 200 CMH. On the other hand, the solutions for 250 and 350 CMH become Pareto dominated in Design #8.

Table 5
Change of an airflow rate

Design	**Air flow rate**	**Initial Invest ment cost (KRW)**	**Operati on cost (KRW/ Yr)**	**PD**	**CO_2 (PPM)**
Non-dominated Solution (Design 4)	100	1,000, 000	182, 400	B	900
Non-dominated Solution (Design 7)	150	1,252, 900	223, 590	A	800
Non-dominated Solution (Design 8)	200	1,569, 700	264, 780	A	700
Dominated Solution	250	1,966, 600	305, 970	A	700
Dominated Solution	350	2,463, 900	388, 350	A	700

- Change in heat exchanger type: The heat exchanger type in Design #8 (Table 3) was varied. As indicated in Table 6, the total heat exchanger was non-dominated.

Table 6
Change of a heat exchanger type

Design	heat exchanger type	Initial Investment cost (KRW)	Operation cost (KRW /Yr)	PD	CO_2 (PPM)
Non-dominated Solution (Design 8)	Total Heat Exchanger	1,569, 700	264, 780	A	700
Dominated Solution	Sensible Heat Exchanger	1,619, 700	826, 450	A	700

It should be noted that the sensible heat exchanger was not selected as shown in Table 3 for several reasons. Since a sensible heat exchanger uses a heat exchanging component made of metal, it is more expensive than a total heat exchanger with a heat exchanging component made of paper. In addition, it has a lower heat transfer efficiency (only sensible heat). One advantage of the sensible heat exchanger is that it has fewer problems with mold growth and dust clogging the filters because it uses metal as a heat exchanging element. However, the aforementioned problems associated with the total heat exchanger can be solved by regular maintenance (replacement) of filters and the heat exchanging component (paper type). Be noted that the cost of filter exchange was included in this study. At a given airflow rate, the sensible and total heat exchanger provides identical PD and CO_2 concentrations, but the sensible heat exchanger requires a higher initial investment cost and provides a lower heat recovery. Thus, any design option using a sensible heat exchanger became dominated by one using a total heat exchanger.

Application in design scenarios

In the previous section, it was shown that all 18 designs were non-dominated Pareto optimal solutions. The advantage of Pareto optimality is that it offers not one but multiple non-dominated solutions, enabling the DM to select his/her preferred design choice (Approach III: search → decide). In other words, there is no need to determine the weights among the objective function elements. As mentioned earlier, the weights can vary according to the DM's preference. Since Pareto optimality is not associated with the issue of weights, the DM is able to select an optimal design of his/her choice from Table 3.

Any building stakeholder (ventilation system engineer, architect, building owner, or occupant) can be the DM. A DM looking for a system with the lowest initial investment cost can select Design #1 or #2. Design #1 is a hybrid ventilation with the air supply diffuser installed in the dining room (60 CMH constant airflow rate fan), and Design #2 uses a 120 CMH constant fan. Note that although Designs #1 and #2 have different airflow rates, they have the same initial investment costs because their exteriors are identical, and only the internal motor and circuit board are different. A DM looking for a system with the lowest operation costs can select Design #1. A DM interested in the lowest PD may select Design #18, which is a combination of the hybrid and total heat exchanger (a hybrid supply diffuser installed in the living room and the dining room, a 60 CMH ventilation fan in the dining room, and 200 and 250 CMH total heat exchangers in the living room and bedroom, respectively). If the initial or operation costs of Design #18 are deemed excessive, the DM can select from other alternatives in Table 3. It should be noted that all designs in Table 3 are non-dominated Pareto optimal solutions. This means that no matter which solution is selected, there is no other solution that dominates it. The case for selecting a system with the lowest CO_2 concentration is not presented here because it is identical to that of selecting the lowest PD.

CONCLUSION AND FUTURE WORK

In this study, it was shown that optimal design of residential ventilation systems in apartment buildings can be achieved using the GA and Pareto optimality with ventilation simulations. The Pareto optimality was used to solve mutually non-compatible objective function elements (initial investment cost, operation cost, PD, and CO_2 concentration). And the GA was used to account for the characteristics of the objective function (discontinuous and non-differentiable problems). The NSGA-II method proposed in Deb (2000) was used to improve the diversity of the optimal solutions. It is automatically executed with integration of the GA and Pareto optimality with the CONTAMW 2.4 simulation in MATLAB. As a result, the DM can choose an optimal solution among the Pareto set according to his/her preference. Future work will include:

- Optimal design for different floor plans and climates: Applying the proposed optimization algorithm to various floor plans such as two bedroom, three bedroom, and four bedroom apartment units as well as different climates.
- Optimal design for different user-scenarios: One of the most difficult problems in building simulation is to predict the occupant's behavior. For further study, an optimal system will be determined based on multiple user scenarios.
- Optimal control: Real-time optimization of ventilation system performance will be a future avenue. This control strategy will integrate current weather information and indoor environmental conditions with the heating and cooling system. The control will be linked to the Internet so that the user can access it from a PDA, wall pad, or any standard web browser.

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