Evolutionary Algorithms for Multi-Objective Optimization in HVAC System Control Strategy

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Abstract - **The supervisory control strategy set points for an existing HVAC system could be optimized using a two-objective evolutionary algorithm. The set points for the supply air temperature, the supply duct static pressure, the chilled water temperature, and the zone temperatures are the problem variables, while energy use and thermal comfort are the objective functions. Different evolutionary algorithm methods for two-objective optimization in HVAC systems are evaluated. It was concluded that controlled elitist non-dominated sorting genetic algorithms offer great potential for finding the Pareto-optimal solutions of investigated problems. The results also showed that the on-line implementation of optimization process could save energy by 19.5%. The two-objective optimization could also help control daily energy use while bringing about further energy use savings as compared to a one-objective optimization.**

I. INTRODUCTION

The performance of the heating, ventilating, and air conditioning (HVAC) system can be improved through the optimization of the supervisory control strategy. The variable air volume (VAV) HVAC system control set points can be adjusted by the supervisor to maximize the overall operating efficiency. Most existing HVAC system processes are optimized at the local loop level; for example, in the existing HVAC system investigated in this paper, which is installed at the Montreal campus of the *École de technologie supérieure* (ÉTS), each local control of an individual subsystem is individually determined, thus leading to the poor performance. The global optimization of these set points can improve the overall operating efficiency. The set points that should be optimized could account for more than 60 variables. The high number of variable problems makes the traditional optimization methods require a sequential, and therefore computationally intensive, approach to find the optimal set of solutions [1]. In addition, since the optimization of a supervisor control strategy should be run on-line at a specific interval (e.g., 15 minutes), the computation must be quite rapid. Using a two-objective optimization algorithm, such as energy use and thermal comfort, could also provide an opportunity to control the thermal comfort and energy use according to the day or

month, thereby bringing about further energy savings [2]. Thus, the optimization of a supervisory control strategy requires a set of solutions put through a single simulation run; in this case, the multi-criterion optimization method is required. From a large number of multi-objective optimization methods, Srinivas and Deb [3] investigated Goldberg's notion of non-dominated sorting in genetic algorithms to find multiple Pareto-optimal points simultaneously. The results of this study showed that the non-dominated sorting genetic algorithm (NSGA) performs better than other investigated methods among three two-objective problems. Deb introduces an elitist non-dominated sorting genetic algorithm (NSGAII) [4]. The simulation results showed that the NSGAII performs better than nine other investigated methods. Therefore, the NSGA and NSGAII are selected and evaluated to solve the HVAC optimization problem. These evaluations are done using the simplified VAV model. However, the optimization of the existing HVAC system is conducted using the detailed and validated VAV model.

II. OPTIMIZATION PROCESS

The real-time, on-line optimization of the HVAC supervisory control strategy is investigated through the optimization of existing HVAC system set points. The air-handling unit (AHU-6) of the existing HVAC systems at the *ÉTS* campus, which meets the load for 70 interior zones on the second floor, is studied. Fig. 1 shows the schematic diagram of this investigated HVAC system.

The performance of this system can be improved through the optimization of its supervisor control strategy. The *"optimized supervisor"* specifies the set points using the optimization process as shown in Fig. 2, which includes (*i*) the VAV model, (*ii*) the two-objective genetic algorithm optimization program, and (*iii*) three main tools, namely, data acquisition, indoor load prediction, and selection tools. The data acquisition tool receives and processes the on-line measured data. The load prediction tool predicts the sensible indoor loads for the optimization period using an on-line measured data of the previous period. Since a set of optimal solutions is obtained by using the two-objective optimization algorithm, the selection tool is used to select the appropriate solution in order to minimize daily energy use.

At each optimization period (e.g., 15 minutes), the genetic algorithm program sends the trial investigated controller set points to the VAV system model, where the energy use and thermal comfort (objective functions) are simulated and returned back to the GAP. The VAV model determines the energy use and thermal comfort resulting from the change in outdoor conditions and indoor loads (independent variables) and controller set points (dependent variables or problem variables). The independent variables (identified by index *IV*) are: the *(i)* the enthalpy of outdoor air $(Ho)_{IV}$, *(ii)* the indoor sensible loads at each zone i $(qs_i)_{IV}$, and *(iii)* the total load of the building $(qt)_{IV}$. However, the dependent variables or problem variables (identified by index *PV*) are: (*i*) the zone temperatures $(Tz_i)_{PV}$, (*ii*) the supply duct static pressure $(Ps)_{PV}$, (*iii*) the supply air temperature $(Ts)_{PV}$, and (*iv*) the chilled water supply temperature $(Tw)_{PV}$. The optimization process shown in Fig. 2 was applied in the optimization calculations of the investigated existing HVAC system whose detailed component models were developed and validated against the monitored data [5].
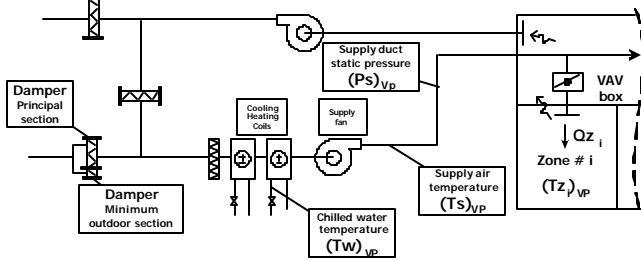

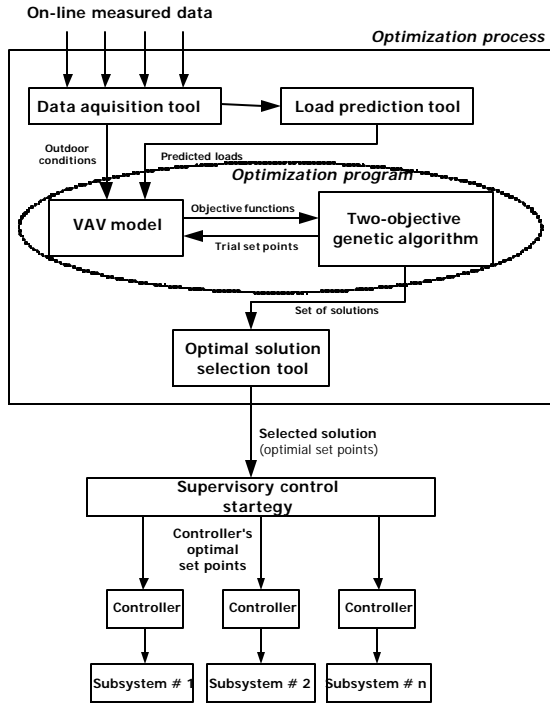Fig. 1 Schematic diagram of the existing HVAC system

Fig. 2 Optimization process including VAV model and optimization program.

The results of this optimization are briefly presented in part B of chapter VI (Results and Discussion) of this paper.

The goals of the two-objective optimization are: (*i*) to find solutions close to true Pareto-optimal solutions and (*ii*) to find solutions that are widely different from each other. To evaluate the candidate evolutionary algorithms, the solutions obtained should be compared with known Pareto-optimal solutions. For that reason, the VAV model was simplified in order to be able to predict the Pareto-optimal front. It was verified that the energy use (objective function) obtained by the simplified model is close to the energy use obtained by the detailed model. In addition, it should be noted that the thermal comfort (second objective function) is the same as in the detailed model.

III. SIMPLIFIED VAV SYSTEM MODEL

In order to evaluate different evolutionary algorithm methods, the water flow rate constraint and energy use calculations (first objective function), including the fan and chiller energy uses, are determined as follows.

A. Fan energy use

The fan energy use ($\overset{\bullet}{Wf}$, kW) is calculated as a function of the fan airflow rate ($\overset{\bullet}{Qf}$, l/s) and total static pressure (fan efficiency equals 0.68). The total static pressure is equal to the static pressure set point ($(Ps)_{PV}$, pa) plus the remaining duct pressure drop, which is a function of the fan airflow rate (sum of the zone airflow rates, $\overset{\bullet}{Qz}$). Applying existing system characteristics, the fan energy use is then given as:

$$\overset{\bullet}{Wf} = \overset{\bullet}{Qf} \cdot \left((Ps)_{PV} + 2 \cdot 10^{-6} \cdot \overset{\bullet}{Qf}^2 \right) / 680000 \qquad (1)$$

where:

$$\overset{\bullet}{Qf} = \sum \overset{\bullet}{Qz_i} = \sum \frac{(qs_i)_{IV}}{1.2 \cdot \left((Tz_i)_{PV} - (Ts)_{PV} \right)} \qquad (2)$$

B. Chiller energy use

The chiller energy is given by the following:

$$\overset{\bullet}{Wc} = \frac{\left[\mathbf{1} \cdot \overset{\bullet}{Qf} \cdot \left((Ho)_{IV} - Hs \right) + (qt)_{IV} \cdot (1 - \mathbf{1}) \right]}{COP} \qquad (3)$$

The outdoor air fraction in the supply air ? is determined using the standard economizer logic:

$$if \ (Ho)_{IV} \geq \left(\frac{(qt)_{IV}}{\overset{\bullet}{Qf}} + Hs \right) then \ \mathbf{1} = 0.2 \ else \ \mathbf{1} = 1 \qquad (4)$$

$$if (Ho)_{IV} \leq Hs \ then \ \overset{\bullet}{Wc} = 0$$

To simplify (3), the following assumptions are made:

    (i)   The air leaving the cooling coil is saturated and its enthalpy (*Hs*) is calculated a function of supply air temperature $(Ts)_{PV}$.

    (ii)   The coefficient of chiller performance (*COP*) could be determined as:

$$COP = 7.9275 \cdot PLR^3 - 21.194 \cdot PLR^2 + 16.485 \cdot PLR + 2.2139 + 0.1 \cdot ((Tw)_{PV} - 6) \qquad (5)$$

where the *PLR* is the part load ratio, which is equal to the ratio of the cooling coil load ($\dot{Q}c$) to the design load (722 kW). It is assumed in the equation above that the *COP* is increased by 0.1 as the chilled water supply temperature $(Tw)_{PV}$ is increased by 1°C. It should be noted that the chilled water supply temperature is limited within [6-11].

C. Water flow rate constraint

The water flow rate, which is used in the constraint verifications (11) presented below, could be determined as follows:

$$\dot{Q}w = \dot{Q}w_{rate} \cdot \left(\frac{\dot{W}c \cdot COP \cdot ((Ts)_{PV} - (Tw)_{PV})}{hw_{rate}} \right)^{1.25} \qquad (6)$$

The water heat transfer coefficient at rating ($h_{w,rate}$) of the investigated existing system is 200186 W/°C, and the water flow rate at rating ($\dot{Q}w_{rate}$) is 33 l/s. The equation above is obtained by assuming that the water heat transfer coefficient (hw) is a function of the water flow rate ($\dot{Q}w$) as follows:

$$hw = hw_{rate} \left(\frac{\dot{Q}w}{\dot{Q}w_{rate}} \right)^{0.8} = \dot{W}c \cdot COP \cdot ((Ts)_{PV} - (Tw)_{PV}) \qquad (7)$$

IV PROBLEM FORMULATION

The optimization seeks to determine the set point values of the supervisory control strategy of the ÉTS system. These set points should be optimized for the energy use and the building thermal comfort. The optimization problem is formed by determining the problem variables, the constraints, and the objective functions. The problem variables are the zone temperatures (70 variables) set points, the supply duct static pressure, the supply air temperature, and the chilled water supply temperature. The resulting problem variables consist of 73 variables. These variables should be determined on-line at each optimization period in order: (*i*) to reduce energy use, and (*ii*) to improve thermal comfort. During the optimization process, the chiller and fan energy uses are determined using the detailed and validated VAV component models. However, in order to evaluate the evolutionary algorithm methods, the energy use is calculated as the sum of the fan and chiller energy uses and using the simplifications presented above.

$$\dot{W}t = \dot{W}f + \dot{W}c \qquad (8)$$

Using (1) and (3), the energy use ($\dot{W}t$) can be determined at each independent variable (*IV*) and proposed problem variable (*PV*).

The zone comfort is represented as the "Predicted Percentage of Dissatisfied" (PPD), and calculated using the following equation:

$$PPD = 100 - 95 \cdot EXP[-(0.03353 \cdot PMV^4 + 0.2179 \cdot PMV^2)] \qquad (9)$$

The predicted mean vote (PMV) is an index devised to predict the mean response of a large group of people according to the ASHRAE thermal sensation scale. In a practical situation, the PMV values tabulated can be used to predict the performance of a VAV system for a combination of variables [6]. In this paper, the zone air velocity is assumed to be fixed at less than 0.1 m/s. The thermal comfort function is then a function of the zone temperatures (i.e., the PPD is equal to 5 for 23.1°C and to 12 for 25°C). The two-objective functions and the constraints could then be represented as follows:

Objective functions:

$$\begin{cases} Min(\dot{W}t) = f1((Ts)_{PV}, (Tz_i)_{PV}, (Ps)_{PV}, (Tw)_{PV}) \\ Min(PPD) = f2((Tz_i)_{PV}) \end{cases} \qquad (10)$$

Constraints:

$$Low\ limits \ \leq \ Problem\ variables \ \leq \ High\ limits$$

$$\begin{cases} 0.3 \cdot \dot{Q}z_{i,max} \leq \dfrac{(\dot{q}t)_{IV}}{1.2 \cdot ((Tz_i)_{PV} - (Ts)_{PV})} \leq \dot{Q}z_{i,max} \\ 0.4 \cdot \dot{Q}f_{des} \leq \dot{Q}f \leq \dot{Q}f_{des} \\ \dot{Q}w \leq 33 \end{cases} \qquad (11)$$

The function f_1 is simplified by (1, 3, and 8) or detailed by the VAV model. The function f_2 is determined by (9). The constraints result from restrictions on the operation of the HVAC system. They cover the lower and upper limits of problem variables: (*i*) the supply air temperature (13–18 °C), (*ii*) the zone air temperature (21–25 °C), (*iii*) the chilled water supply temperature (6–11 °C), and (*iv*) the static pressure (150–250 Pa). The constraints also cover the design capacity of components. The fan airflow rate is restricted within the design ($\dot{Q}f_{des} = 2300 l/s$) and minimum limit ($0.4 \cdot \dot{Q}f_{des}$). The zone airflow rates are also restricted within the maximum ($\dot{Q}z_{i\,max}$) and minimum limits, which are equal to 30% of design airflow rate ($0.3 \cdot \dot{Q}z_{i\,des}$). The maximum limit could be determined as follows:

$$\dot{Q}z_{i,\max} = \dot{Q}z_{i,des} \cdot \sqrt{\frac{(Ps)_{PV}}{Ps_{des}}} \qquad (12)$$

The design static pressure (Ps_{des}) of the investigated system is 250 Pa and the design airflow rate at each zone i ($\dot{Q}z_{i_{des}}$) is known.

V. OPTIMIZATION ALGORITHM

A. Genetic algorithm

In this study, a genetic algorithm (GA) search method based on the mechanics of Darwin's natural selection theory was developed in order to solve the optimization problem. Since energy use and thermal comfort are the objective functions, the multi-objective optimization must be investigated. In this paper, the NSGA and NSGAII are investigated and evaluated for solving the HVAC optimization problem.

The NSGAII uses the elite-preserving operator, which favors the elites of a population by giving them an opportunity to be directly carried over to the next generation. After two offspring are created using the crossover and mutation operators, they are compared with both of their parents to select two best solutions among the four parent-offspring solutions. The NSGAII employs the crowded tournament selection operator [6]. As a result of the constraint functions, a penalty must be imposed on the objective functions. The constraint violation is calculated using the penalty function approach. The penalty parameters are set at 100 and 5 for energy use and thermal comfort objective, respectively. The simulated binary crossover operator (SBX) is used here to create two offspring from two-parent solutions. The random simplest mutation operator is applied in order to randomly create a solution from the entire search space.

The NSGA uses both the non-dominated sorting strategy and the sharing strategy (niche method) before the reproduction operator. The crossover and mutation operators remain as usual (as in the NSGAII described above). The idea behind the non-dominated sorting procedure is that a ranking selection method is used to emphasize good solutions while a niche method is used to maintain stable subpopulations of good points.

B. Comparison of two-objective optimization methods

Since many two-objective optimization methods are available, it is natural to ask witch of them performs better when compared to other algorithms on the investigated problem (HVAC problem). The performance of these optimization methods is evaluated through the HVAC problem presented in (10 and 11). In these evaluations, the following two performance metrics are used: (*i*) metric evaluating the closeness to the Pareto-optimal front, and (*ii*) metric evaluating diversity among non-dominated solutions. In the first metric, the distances of the solutions obtained from the Pareto-optimal solutions are calculated and divided by the number of solutions. In the second one, the *Spread* metric [4] is used, considering the distance between neighboring solutions and extreme solutions located on the Pareto-optimal front.

C. Pareto-optimal solutions

In order to compare the different optimization methods, the Pareto-optimal solutions, which vary with the independent variables, should be known. At each optimization period, the Pareto-optimal solutions corresponding to these independent variables (*IV*) are obtained. The optimal supply air temperature set point, which has the greatest effect on the energy use objective function, is at its minimum possible value while all constraints in (11) are respected. The optimal zone temperatures vary within the range [23.1 - 25°C]. The optimal static pressure should be at its lowest possible level while constraint 2 in (11) is respected. The optimal chilled water supply temperature is at its highest possible value while the water flow rate is less than 33 l/s, and constraint 4 in (11).

VI. RESULTS AND DISCUSSION

A. Comparison results

The comparison is achieved at three different optimization periods (summer, midseason, and winter), but only one summer day period is presented here. In this case, the enthalpy of outdoor air is assumed to be 71.25 kJ/kg (this corresponds to an outdoor temperature of 28°C and a relative humidity of 70%). The fraction of outdoor air in the supply air (?) is 0.2. The NSGA and NSGAII program is executed for 100 generations, with a population size of $p_z = 50$, and with different parameters. The best parameters, which are: crossover probability $p_c = 0.9$ and distribution index $?_c = 4$, mutation probability $p_m = 0.04$, and NSGA sharing value S_{share} 0.15X, are only presented. Fig. 3 shows the optimal solutions obtained by NSGA after 100 generations, while Fig. 4 shows the optimal solutions obtained by NSGAII after 100 generations. The Pareto-optimal solutions front is presented in the two figures. The spread and the distance are determined for two programs, as shown in Table 1. The NSGAII performs better for this HVAC problem with the parameters mentioned above.

If the initial solutions are not properly selected, premature convergence may occur. Assuming that all initial supply air temperatures values are higher than 14°C, with high exploitation, the crossover operator may not be able to find the new solution in the supply air temperature direction as shown in Fig. 5 and Fig. 6, and premature convergence is observed. In order to overcome this problem, the mutation operator probability could be increased, but the good solutions obtained could be deteriorated. Deb proposes the NSGAII with a controlled elitist operator for better convergence [8]. By applying the controlled elitist operator, the NSGAII produces a better convergence and distribution of solutions.
Fig. 7 shows the solutions obtained by a controlled elitist NSGAII. The true optimal solutions are found using a controlled elitist NSGAII with higher than 200 generations. The

controlled NSGAII is therefore used to solve the investigated HVAC problem.
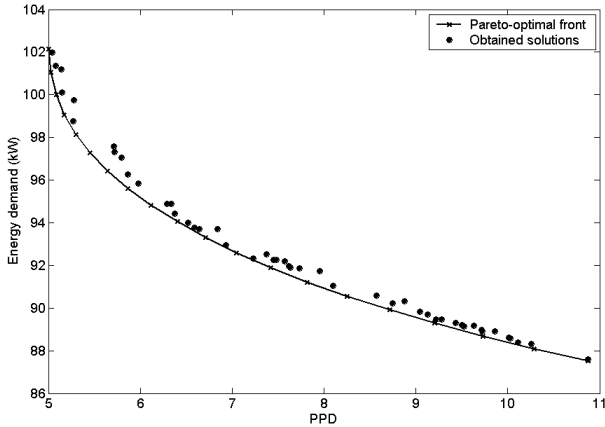

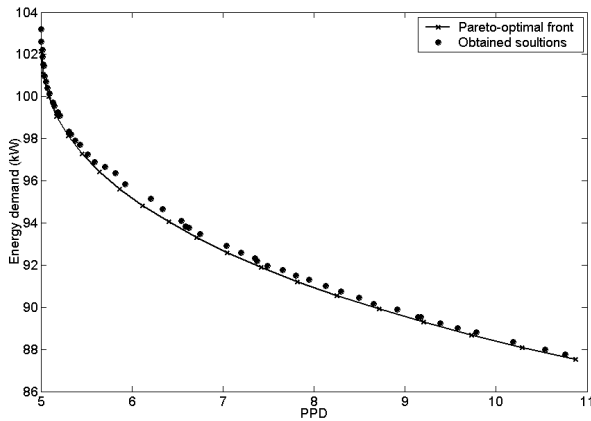Fig.3 Optimal solutions obtained by NSGA after 100 generations

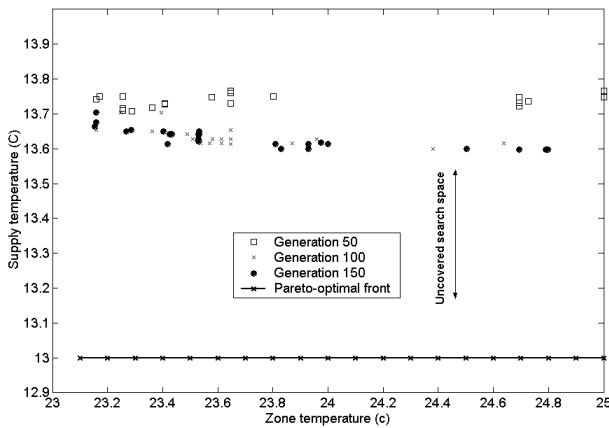Fig.4 Optimal solutions obtained by NSGAII after 100 generations

Fig.5 Search for optimal supply air temperature (13°C) in decision space using NSGAII, the crossover with low probability of mutation operator cannot find real optimal solution.

TABLE I
METRIC PERFORMANCE FOR INVESTIGATED GA METHODS

Type	NSGAII	NSGA
Spread	0.4312	1.2651
Distance	0.3465	0.7278

B. Application results

The optimization process shown in Fig. 2 using the controlled elitist NSGAII is applied to the existing HVAC system. As mentioned earlier, the detailed and validated VAV model is used here. The actual energy use was determined through monitoring data and appropriate validated models. To compare the optimal and actual energy demands, only one solution for each optimization period was selected among the set of solutions considered. This solution has the same PPD as the PPD obtained from the monitored data. Fig. 8 shows this comparison of the actual and optimal energy demand for the same PPD on July 29, 2002. The energy demand of the optimized control strategy is less than that of the actual one. The energy saved by optimization is 18.8% for July 29, and 19.5% for July 25 to 31.
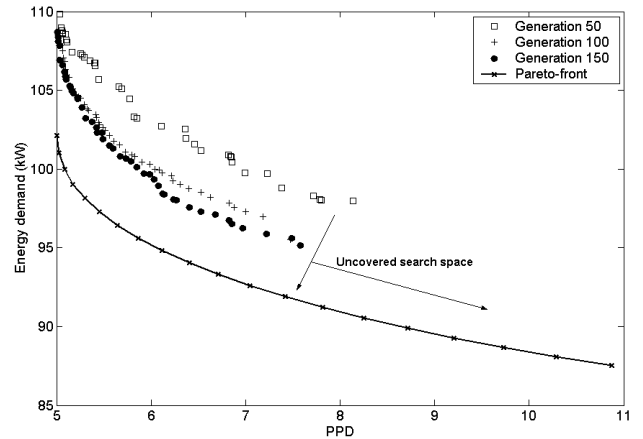

Fig. 6 Search for optimal Pareto-optimal front in objective space using NSGAII when the initial solutions are not properly selected, and with low probability of mutation.
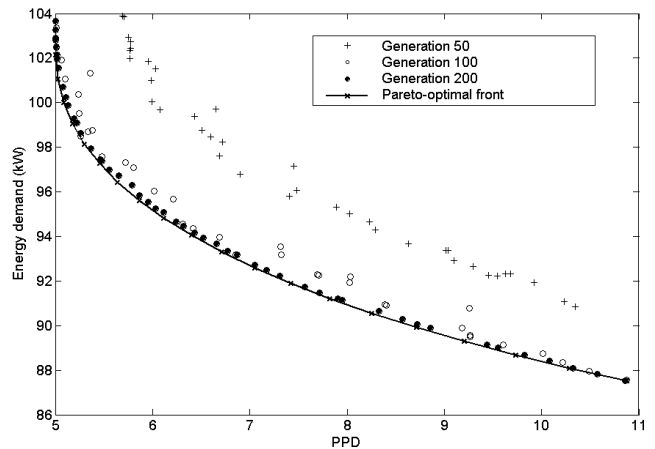

Fig. 7 Search for optimal Pareto-optimal front in objective spaces using controlled NSGAII when the initial solutions are not properly selected, and with low probability of mutation

The thermal comfort is presented in this study as the objective function, but the optimization problem could be solved by defining the thermal comfort criterion as the constraint. The only optimal solution would then be obtained, having a high PPD limit. The advantage of using a two-objective scheme is to minimize daily energy use through the

fluctuation of the building PPD during occupied periods, taking into account the required energy demand.

This is achieved by using the selection tool, as shown in Fig. 2. For July 29, the energy demand is 43 kW for a PPD of 9.8% and 46.4 kW for a PPD of 5.1% at 4:00 PM. To improve the thermal comfort from 9.8 to 5.1%, it needs 3.4 kW. However, in the morning, it needs only 1.6 kW. The optimal selection tool using the strategy described next selects a low PPD in the morning and a high one in the early afternoon. At each period, the selection tool selects the solution requiring the least energy use (extreme right solution in Fig. 7). The additional energy use required for improving the thermal comfort PPD from one selected solution to the next is determined and compared with the permission set point recorded by the operator in the selection tool (*e* kW/PPD). If this further energy use requirement is lower than the permission set point, the next solution will be selected; otherwise the first solution is, and so on, for all the solutions. This strategy could be applied only by using the two-objective problem, which ensures the evaluation of a set of optimal solutions at each run.

To evaluate the optimization results of the existing VAV system using the one-objective and the two-objective problems, different permission set point values are selected in the selection tool during occupied periods. Daily energy use and daily thermal comfort (*PPD*) are calculated and illustrated as a function of the permission set point in Fig. 9. The curves *K* and *J* represent optimal solutions using the two-objective and one-objective optimization algorithms, respectively. The 2% energy use savings could be obtained using a two-objective optimization algorithm as compared to the one-objective optimization scheme applied to the same daily PPD. (11).

VI. CONCLUSION

The supervisory control strategy set points are optimized using a two-objective genetic algorithm. The set points are optimized for existing HVAC systems. The evolutionary algorithm program required in the optimization process is also selected and evaluated. These evaluations performed using the metrics evaluating closeness to the Pareto-optimal front and evaluating diversity among non-dominated solutions are realized with the simplified VAV model. The results of the evaluation of evolutionary algorithms show that the controlled NSGAII produces better convergence and distribution of optimal solutions located along the Pareto front. The optimization process using the controlled elitist NSGAII was applied to the existing HVAC system using the detailed VAV model. The energy demand of the optimized control strategy is less than that of the actual one by 19.5% for July 25 to 31. Other results indicate that the application of a two-objective optimization algorithm could help control daily energy use or daily building thermal comfort while providing further energy use savings as compared to the one-objective optimization approach.
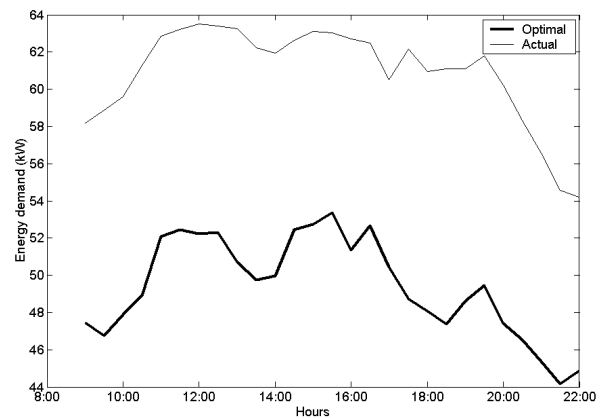

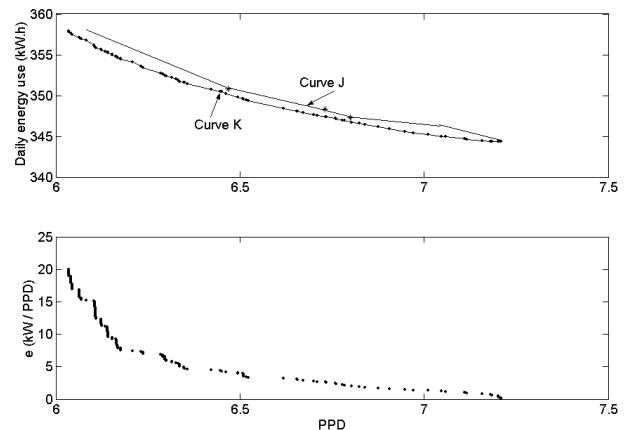Fig.8 Actual and optimal energy demands for July 29, 2002

Fig. 9 Optimal daily energy use obtained by two-objective selection tool (curve K) and one-objective optimization (curve J) for existing HVAC system

REFERENCES

[1] J. Wright, H. Loosemore, and R. Farmani, "Optimization of building thermal design and control by multi-criterion genetic algorithm," *Energy and buildings*, vol. 34, pp. 959-972, 2002.

[2] N. Nassif, S. Kajl, and R. Sabourin, "Two-objective on-line optimization of supervisory control strategy," *Building Serv. Eng. Technol.*, in press.

[3] N. Srinivas and K. Deb, "Multi-objective function optimization using non-dominated sorting genetic algorithms," *Evolutionary Computation,* vol. 2(3), pp. 221-248, 1994.

[4] K, Deb, S. Agrawal, S. Pratap, and T Meyarivan, "Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II," *LNCS*, vol. 1917, pp. 849-859, 2000.

[5] N. Nassif, S. Kajl, and R. Sabourin, "Modelling and validation of existing VAV system components," submitted to *Proceedings of e.Sim Conference*, Vancouver, June, 2004.

[6] K, Deb, *Multi-objective optimization using evolutionary algorithms*, 1st ed., New York: John Wiley & Sons, 2001.

[7] PO. Fanger, *Thermal comfort: analysis and applications in environmental*, New York: McGraw-Hill, 1970.

[8] K, Deb and T. Goel, "Controlled elitist non-dominated sorting genetic algorithms for better convergence," *LNCS*, vol. 1993, pp. 67-81, 2001.