Multi-variable Optimization of HVAC System Using a Genetic Algorithm

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Abstract: Geothermal is a fast-growing alternative heat source for HVAC systems, however, the initial cost of using a ground source HVAC system is higher compared to an air source system. Studies about system design and operation are necessary to reduce the initial cost and ensure that the ground source heat pump system has high efficiency, resulting in a lower total life-time cost. In this study, a multi-variable evolutionary computation algorithm is proposed for generating optimal parameters for a geothermal source HVAC system. The system was modeled and simulated using MATLAB. The design parameters were calculated by minimizing the energy consumption. Based on an experimental building, a case study was presented. Using this model, the optimal set points were calculated and used as a designed system. Energy consumption of this system was reduced by about 10% compared to the system operated with a fixed supply cold water temperature (7 °C).

Key words: Ground source air-conditioning system, genetic algorithm, optimization, MATLAB.

1. Introduction

Geothermal is a widely available and increasingly utilized source of sustainable and renewable energy. Development of geothermal energy not only means the elimination of pollutants such as particulates and greenhouse gases but also reduction in heat island effect [1-3]. Unfortunately, due to the expense and effort to bury heat exchangers in the ground or providing wells for the energy sources, the initial capital cost of using ground source heat pumps is about 30%-50% higher than air source heat pumps [4]. Therefore, thorough research and calculations are required when designing systems with geothermal heat sources to reduce the initial cost and ensure that the ground source heat pump system has high efficiency, resulting in a lower total life-time cost. The performance of the system depends largely on the ground source heat pump’s properties such as temperature of supplied cold water, cooling water temperature, heat pump capacity, PLR, etc. Furthermore, in use, the performance of HVAC systems connect strongly with operating set points and schedule. For an installed HVAC system, the cold water supply temperature is a set point that can be controlled easily.

In this study, we use a genetic algorithm method to find the optimal design of a geothermal heat pump air-conditioning system. Genetic algorithms have been used in building applications related to energy consumption, mostly to optimize the sizing and control of HVAC systems [5-8]. It has also previously been used in ground source heat pump design and component selection [9].

We built a model based on the HVAC system in our experimental building, which was designed for zero-energy consumption and built at the University of Tokyo [10]. In this building, a ground source cooling/heating system is utilized. Currently, we are working on finding the best operating schedule to
minimize the energy consumption of the system [11]. Here, the authors present the model for optimal set points calculation.

2. Research Methods

2.1 System Configuration

Based on the experimental building, we built our simulation model in MATLAB. Models of BHE (borehole heat exchangers), a FCU (fan coil unit) and a GSHP (ground source heat pump) chiller were implemented in the simulation model (Fig. 1).

![Fig. 1 System configuration.](image)

2.2 Problem Formulation

This model was built based on mathematical models of the components in TRNSYS [12], and various equipment catalog data. For any cooling load, the objective of the problem is to minimize total power consumption of the GSHP air-conditioning system $E_{total}$ while ensuring that the temperature of the air supplied by the FCU $T_{air,out}$ and the temperature of cooling water returning to the ground heat exchangers $T_{cw,in}$ stays within their constraint range. That is:

$$
\text{Minimize} \quad E_{total}(E_{chiller}, E_{pump}, E_{fan})
$$

Subject to:

$$
T_{air,out} \in [T_{air,min}, T_{air,max}], \quad T_{cw,in} \in [T_{cw,min}, T_{cw,max}]
$$

Here, the objective function $E_{total}$ is expressed by Eq. (1).

$$
E_{total} = E_{chiller} + E_{pump} + E_{fan}
$$

where, the expressions for energy consumption of GSHP chiller $E_{chiller}$, pumps $E_{pump}$ and fan $E_{fan}$ follow Eqs. (2)-(4), respectively.

$$
E_{chiller} = \frac{Q_{load}}{\text{COP ratio}} \times \text{COP nom}
$$

$$
Q_{load} = m_{cw} C_{pw} (T_{cw,in} - T_{cw, set})
$$

| Table 1  Model nomenclature. |
|-----------------------------|-------------------|
| $Q_{load}$  | Current load on the chiller |
| $E_{total}$ | Total power consumption of the GSHP air-conditioning system |
| $E_{pump}$  | Energy consumption of pumps |
| $T_{cw,in}$ | Temperature of cooling water returning to the ground heat exchangers |
| $E_{chiller}$ | Energy consumption of GSHP chiller |
| $T_{air,out}$ | Temperature of the air supplied by the FCU |
| COP ratio | Ratio between chiller COP at current conditions and the nominal COP |
| $m_{cw}$ | Cooling water flow rate |
| $T_{chw,set}$ | Temperature of supplied cold water of chiller |
| $n_{f}$ | Total efficiency of cold water pump |
| $n_{l}$ | Total efficiency of cold water pump |
| $\eta$ | Total efficiency of cooling coil fan |
| $C_{pw}$ | Specific heat of cold water |
| $\rho_{air}$ | Air density |
| $d_{0} \sim d_{6}$ | Constant coefficients |
| $c_{0} \sim c_{3}$ | Constant coefficients |
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\[ \text{COP}_{\text{ratio}} = a_0 + a_1(\text{PLR}) + a_2(\text{PLR})^2 + \cdots + a_6(\text{PLR})^6 \]  
\[ \text{COP}_{\text{nom}} = b_0 + b_1(\text{T}_{\text{chw, set}} / (\text{T}_{\text{cw, out}} - \text{T}_{\text{chw, set}})) \]

\[ + b_2((\text{T}_{\text{chw, set}} / (\text{T}_{\text{cw, out}} - \text{T}_{\text{chw, set}}))^2 \]  
\[ \text{PLR} = \frac{Q_{\text{load}}}{Q_{\text{capacity}}} \]  
\[ Q_{\text{capacity}} = (c_0 + c_1\text{T}_{\text{chw, set}} + c_2\text{T}_{\text{chw, set}}^2 + c_3\text{T}_{\text{chw, set}}^3)\text{Capacity}_{\text{rated}} \]  

Eqs. (2c) and (2d) are formulated based on catalogue values shown in Fig. 2.

\[ E_{\text{pump}} = m_{\text{chw}}s_{\text{chw}}H_{\text{chw}} / \eta_1 + m_{\text{cw}}s_{\text{cw}}H_{\text{cw}} / \eta_2 \]  
\[ m_{\text{chw}} = (d_0 + d_1Q_{\text{load}} + d_2Q_{\text{load}}^2)(d_3 + d_4T_{\text{chw, set}}^2) \]

\[ + d_5T_{\text{chw, set}}^2 + d_6T_{\text{chw, set}}^3 \]  
\[ H_{\text{chw}} = e_0 + e_1m_{\text{chw}} + e_2m_{\text{chw}}^2 \]  
\[ H_{\text{cw}} = f_0 + f_1m_{\text{cw}} + f_2m_{\text{cw}}^2 \]  

Eq. (3b) is based on a set of experimental data shown in Fig. 3 [13].

\[ E_{\text{fan}} = m_{\text{air}}H_{\text{air}} / \rho_{\text{air}} / \eta_3 \]  
\[ H_{\text{air}} = i_0 + i_1m_{\text{air}} + i_2m_{\text{air}}^2 \]  

The equations above describe the optimization problem. In these formulations, \( Q_{\text{load}} \) and \( \text{Capacity}_{\text{rated}} \) are external variables which will be used as free input parameters. \( m_{\text{air}}, T_{\text{chw, set}} \) and \( m_{\text{cw}} \) are parameters that need to be designed, here we let them be set points of the system during optimization. Other parameters can be collected from experimental data and catalog data. Consequently, the optimization problem can be rewritten as Eq. (5).

\[ \text{Minimize}_{T_{\text{chw, set}}, m_{\text{air}}, m_{\text{cw}}} E_{\text{total}}(Q_{\text{load}}, m_{\text{air}}, T_{\text{chw, set}}, m_{\text{cw}}, \text{Capacity}_{\text{rated}}) \]  

The above described optimization problem has many discrete variables and non-linear equations in different variables. To solve this problem, an AGA (adaptive genetic algorithms) method [14] is adopted.

2.3 Optimization Algorithm

In GA, the probabilities of crossover \( P_c \) and mutation \( P_m \) greatly determine the degree of solution accuracy and the convergence speed that genetic algorithms can obtain. Instead of using fixed values of \( P_c \) and \( P_m \), AGA utilize the population information in each generation and adaptively adjust \( P_c \) and \( P_m \) based on the fitness values of the solutions and defined coefficients \( k_1 \sim k_4 \) in order to maintain the population diversity as well as to sustain the convergence capacity [14]. In this study, the fitness function is the total energy consumption of the system. The variables \( T_{\text{chw, set}}, m_{\text{air}}, m_{\text{cw}} \) are encoded into binary strings which form a chromosome. The ranges of parameters are limited by pre-defined constraint conditions.

3. Case Study

To show how the above optimization model can be applied, we simulate a GSHP system with one room, one GSHP chiller, one cold water pump and one cooling water pump.

3.1 Calculation Conditions

The AGA was run with the parameters summarized in Table 2. The cooling load is shown in Fig. 4. It is the cooling load of a 100 m\(^2\) classroom in our experimental building on a typical August day. The maximum cooling load is 8.6 kW and the cooling time is 9 h. The rated capacity of the chiller is 11 kW.
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3.2 Optimal Design

First, using the maximum cooling load and the rated capacity of 11 kW as conditions our AGA found the optimal set points with the minimum energy consumption of 1.9 kW (Table 3). We see, the system is optimal designed with $T_{chw, set} = 13 \, ^\circ C$, $m_{air} = 3,700 \, m^3/h$ and $m_{cw} = 41 \, L/min$.

Then, summation of system energy usage over one day are compared using an optimal case, case 1 and case 2 (Table 4). In case 1, all the set points, $T_{chw, set}$, $m_{air}$ and $m_{cw}$ are fixed to the optimization results in Table 3 to check the performance of this optimal designed system. Then in case 2, the $T_{chw, set}$ was changed from 13 °C to 7 °C and other parameters were set as the same value in Table 3 to check the sensitivity of the system total energy usage to $T_{chw, set}$.

To check the performance difference between this optimally designed system and a system operated with dynamic optimal set points, we calculated an optimal case. In this case, all the set points were found by optimization calculations for each given hourly cooling load value (Fig. 4); again, the energy consumption of the system was used as the objective function.

The results in Fig. 5 show that the energy consumption in Case 1 is almost the same as in the optimal case. Meanwhile, the optimally designed system with $T_{chw, set} = 7 \, ^\circ C$ in case 2 results in the energy usage increasing by 10%. The dynamic optimization set points for the optimal case is shown in Fig. 6. In the optimal case, except at 8:00 and 17:00 the $T_{chw, set}$ is 12.5 °C or 13 °C which is very close to or equal to the set temperature used in case 1. Furthermore, the chiller uses about 80% energy of the system total energy consumption in all 3 cases (Fig. 7).

3.3 $E_{total}$ vs $T_{chw, set}$ and PLR

Fixing $m_{air}$ and $m_{cw}$ at the optimal values in Table 3, we calculated a day total energy consumption of the system with different temperature in a range of 7~15 °C. To compare the energy consumption with different $Capacity_{rated}$ and PLR we calculated a unit capacity case, case 3 and case 4 (Table 5). In the unit capacity case, the $Capacity_{rated}$ was 11 kW and in case 3 and case 4 it was 1.2 times and 1.4 times larger, respectively.

The results in Fig. 8 show that $E_{total}$ for the day is decreasing when $T_{chw, set}$ is increasing from 7 °C to 13 °C, then increasing slightly as the temperature changes from 13 °C to 15 °C. The energy consumption was higher in case 3 and case 4 compared to the unit capacity case. This is because the PLR in case 3 and case 4 are lower than for the unit capacity case as shown in Fig. 9. PLR was about 50%-60% in the unit capacity case and 30%-50% in case 3 and case 4.
Table 2  AGAs parameters.

| Population size | Probabilities of crossover and mutation | Maximum generation |
|-----------------|------------------------------------------|-------------------|
| 200             | $k_1, k_2$ 0.01 $k_3, k_4$ 0.04         | 1,200             |

Fig. 4  Cooling load.

Table 3  Optimal design.

| Calculation conditions | Optimal set points | Optimization results | Minimum |
|------------------------|--------------------|----------------------|---------|
| $Q_{\text{load}}$      | $T_{\text{chw, set}}$ | $m_{\text{air}}$     | $m_{\text{cw}}$ | $E_{\text{total}}$ |
| 8.6 kW                 | 13 °C              | 3,700 m$^3$/h        | 41 L/min | 1.9 kW              |

Table 4  Calculation cases.

| Case 1 | Case 2 | Optimal case |
|--------|--------|--------------|
| $T_{\text{chw, set}}$ | Table 3 | Fixed at 7 °C | Dynamic optimization |
| $m_{\text{air}}, m_{\text{cw}}$ | Table 3 | Table 3 | Dynamic optimization |

Fig. 5  Energy consumption over one day of operation for case 1, case 2 and optimal case.

Fig. 6  Optimal set points of optimal case.
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Fig. 7  Chiller electricity consumption vs. pumps & fan electricity consumption.

Table 5  Calculation cases.

| Unit capacity case | Case 3 | Case 4 |
|--------------------|--------|--------|
| Capacity rated     | 11 kW  | 13.2 kW| 15.4 kW|
| m_{air}, m_{cw}    | Table 3|        |

Fig. 8  Energy consumption as a function of cold water temperature and heat pump capacity.

Fig. 9  PLR over the course of a day for different capacity cases.

4. Conclusions

In this study, a system consisting of BHE (borehole heat exchangers), a water-to-water heat pump and a FCU (fan coil unit) was modeled and simulated using MATLAB. A multi-variable evolutionary computation algorithm was proposed for generating optimal parameters for the system. As a result, an optimal system was designed with parameters that were calculated by minimizing system energy consumption. Energy consumption of the system was about 10% lower than the system operated with a fixed supply cold water temperature (7 °C). Further result showed that the energy consumption increase due to decreasing PLR when the capacity is increased.

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