GENETIC ALGORITHMS AS AN OPTIMISATION TOOL FOR HVAC DESIGN

L'ALGORITHME GÉNÉTIQUE COMME OUTIL D'OPTIMISATION POUR LA CONCEPTION D'UN CLIMATISATEUR

GENETISCHE ALORITHMEN ALS OPTIMIERUNGS-METHODE FUER DIE BEMESSUNG EINER KLIMAANLAGE

Alan Dunn*

Summary
Genetic algorithms are introduced as a tool for solving parametric optimisation problems, and their previous use in engineering applications is reviewed. The fundamental genetic operators for reproduction, crossover and mutation are described and current areas of research indicated. Results are presented for an experiment carried out to evaluate the performance of genetic algorithms in optimizing the design of a variable air volume air conditioning system. The mathematical model of the system is described, as is the method of evaluating system performance. It is found that the genetic algorithm can easily be interfaced to an external simulation programme and that the optimum combination of design parameters is found within 3% of the time necessary to perform an exhaustive search.

Résumé
L'algorithme génétique est présenté comme un outil pour résoudre les problèmes d'optimisation paramétrique. Ses applications en ingénierie sont passées en revue. Les trois opérateurs génétiques fondamentaux, c'est à dire de réproduction, de croisement et de mutation sont décrits et les sujets de recherches actuels concernant l'algorithme génétique sonts mentionés. Les résultats présentés concernent une expérience menée pour evaluer la performance d'un algorithme génétique en vue d'optimiser la conception du système de climatisateur VAV (à débit variable). Le modèle mathématique est décrit de même que la méthode d'évaluation de la performance du système. Cette étude conclut que l'alogrithme génétique peut être facilement connecté à un logiciel de simulation, et que le temps nécessaire pour localisé la combinaison optimum des paramètres conceptuels représente 3% du temps utilisé pour une recherche exhaustive.

Zusammenfassung
Genetische Algorithmen werden als Methode zur Loesung parametrischer Optimierungsprobleme vorgestellt. Nach einem Ueberblick ueber ihre bisherige Anwendung im Ingenieurwesen wird ausfuehrlich ueber eine Untersuchung berichtet, welche durchgefuehrt wurde, um den Einsatz von genetischen Algorithmen fuer die Optimierung der Bemessung einer zentralen Klimaanlage mit variablem Luftvolumenstrom zu erproben. Das mathematische Klimatisierungsmodell wird beschrieben, ebenso die Methode fuer den Vergleich der erhaltenen Bemessungswerte. Es stellte sich heraus, dass der genetische Algorithmus auf einfache Weise mit einem bestehenden Simulationsprogramm gekoppelt werden kann und dass die optimale Kombination der Bemessungswerte innerhalb von 3 % der Zeit, welche fuer eine Auswertung aller moeglichen Kombinationen notwendig ist, gefunden werden kann.

* *Faculty of Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong*

Introduction

The design of heating, ventilating and air conditioning (HVAC) systems generally involves the selection of predesigned components and the choice of appropriate parameters to ensure that the components interface correctly and that the system gives the desired overall performance. The complete set of component parameters would in fact specify a particular design. Usually, there are many sets of parameters that produce a working solution, but only one which results in a globally optimal solution. An engineer rarely has time to search for this global optimum and is usually content to find a reasonable working solution. In place of optimisation procedures, rules of thumb are used to select the design parameters.

Analytical optimisation techniques are used widely in other fields of engineering, but these methods are difficult to apply to HVAC systems where search spaces are large, non-linear, discontinuous, and heavily constrained. (1,2)

The introduction of genetic algorithms (GA) is generally attributed to John Holland (3) and from a small beginning has developed into a major area of international research. The recent rapid growth of interest in GAs has arisen from, amongst other things, their use to train neural networks, and their inherent suitability for parallel processing.

GAs use a random search method in which a number of solutions are considered simultaneously, and the search itself is guided by probabilistic transition operators based on Darwinian survival of the fittest principles.

GAs have been used to optimize the operation of a pipeline (4) in which the correct combination of pumps is selected to minimize energy consumption whilst maintaining the pressure distribution along the pipeline within specified limits. GAs have also been used to determine the optimum cross sectional areas for each member of a lattice beam (5); to optimize flight trajectories (6); and to layout network diagrams (7).

The objective of the present study is to examine the suitability of genetic algorithms to assist in the design and optimisation of HVAC systems.

Description of the air conditioning system

A variable air volume (VAV) air conditioning system was selected as a vehicle with which to evaluate the use of genetic algorithms. The system comprises an air handling unit with chilled water cooling coil and variable speed supply fan serving a single floor of a high rise office building. No return air fan is used and return air enters the plant room via a wall transfer grille where it mixes with a constant, minimum fresh air supply before entering the air handling unit. A central refrigeration system provides chilled water to the cooling coils on each floor.

Mathematical model of the air conditioning system

A simple, steady state model was developed to predict the performance of the VAV system under *design* operating conditions. The decision to optimize only for the design case was made to reduce the simulation time and hence allow an exhaustive search of the parameter space to be carried out. However, with a binned boundary condition input file the mathematical model will readily calculate both peak loads and annual performance.

The model requires the following boundary conditions to be specified:

t_{ao} design outside air dry bulb temperature, ^{o}C

g_{ao} design outside air moisture content, kg kg^{-1}
ΣQ_s peak block sensible cooling load, kW
ΣQ_l peak block latent cooling load, kW
m_{fa} minimum fresh air mass flow rate, kg s^{-1}

A large number of design parameters were considered for inclusion in the optimisation study, from which the following three were selected:

Δt_s design supply air temperature differential, K
β cooling coil contact factor, -
t_{ai} design room air temperature, ^{o}C

Details of the equations used in the model are given in Appendix 1. An iterative solution of these psychrometric equations describing each process yields the vector of system state points (i.e. the temperature and moisture content at each point in the system).

Although a faster execution speed could be achieved by embedding the simulation programme as a subroutine within the genetic algorithm itself, it was in fact implemented as a separate executable programme with data exchange taking place via ASCII files. This structure allows the genetic algorithm to be used to drive other simulation programmes without modification to the source code. It must be emphasized that the simulation model is quite independent of the genetic algorithm, all that is required of the model is that it can take a set of design parameters as input and from these calculate the resulting system performance with sufficient accuracy. The model can be steady state or dynamic as the designer thinks appropriate.

System evaluation
The method of system evaluation is independent of the genetic algorithm itself; all that is required is that the evaluation method should produce a single numerical index, the system fitness, that may be used to rank alternative designs. The evaluation of system performance must be related to the nature of the application and to the clients wishes: different emphasis will be placed on the various criteria under different circumstances. Capital and running costs may be easily calculated and the net present value cost determined for each system: the fitness of a system would then be inversely proportional to its cost. However it is often necessary to account for non-financial factors such as aesthetic appearance, or user comfort. Most optimisation methods, including genetic algorithms, require that all relevant assessment criteria be combined so that an overall value of objective or fitness may be assigned to each solution. This would appear to be another area in which the ubiquitous expert system might usefully be applied. The ability to manipulate both numeric and symbolic data would give more flexibility to the evaluation process as compared with the simple weighted objective function used here.

Usually there are constraints within the search space which limit the range of feasible solutions, (maximum physical size, maximum velocities based on acoustic requirements, etc.). For the air conditioning system considered here, the range of design parameters selected results in a continuous, unconstrained search space and no special treatment was required. The problem of handling constraints within genetic algorithms is currently an active area of research and although no clear consensus has been reached, the most widely used approach is to introduce a penalty function into the assessment of fitness (8).

A procedure was written which takes as its input the state point vector determined by the system model, and calculates V_s the supply air volume flow rate (which strongly influences the size, and hence capital cost, of all air side equipment), Q_c the cooling coil duty (which strongly influences the capital cost of the refrigeration plant and chilled water pipework), and Q_e the electrical input power to the fan and refrigeration compressor (taking account of the influence of chilled water supply temperature on refrigeration plant efficiency). Each of these terms were normalized by dividing by a scaling factor S_n corresponding to a standard or mean value for each term, and then multiplied by a weighting factor, w, which expresses the relative importance placed on each term during the optimisation. The value of the weighting factor would be decided by the designer and would reflect her view of the relative importance within the context of the current project. The fitness f_n of a member of the population is then given by:

$$f_n = \left\{ \frac{w_1}{S_1} V_s + \frac{w_2}{S_2} Q_c + \frac{w_3}{S_3} Q_e \right\} \tag{1}$$

Genetic algorithm

The implementation of a genetic algorithm requires that the set of parameters to be manipulated during the search process be coded as a finite length string. The most widely used representation is a binary string, however researchers are experimenting with other representations including strings of floating point numbers (9). This string is analogous to a chromosome that encodes all the design parameters of a particular system.

Each of the three design parameters manipulated during the optimisation were mapped to a 4 bit binary string, or gene. For example, the value of coil contact factor, is mapped as follows:

$$\text{Gene} = \frac{\beta - \beta_{min}}{\beta_{max} - \beta_{nub}} (2^4 - 1) \tag{2}$$

Where β is the value of contact factor to be mapped and where β_{min} and β_{max} are the user defined limits. It can be seen that a contact factor of 0.83 would therefore be encoded as:

$$\text{Gene} = \frac{0.83 - 0.80}{0.98 - 0.80} \times 15 = 2.5 = 0010_B \tag{3}$$

Each of the three genes are then concatenated to form a 12 bit binary string, or chromosome. This results in a three dimensional search space of size 16^3, and where each of the 4096 points represents a combination of parameters that would yield a feasible design for the VAV system.

The starting point for the search is to randomly generate an initial set, or population of 12 bit binary strings. Each string is decoded and the parameters passed to the simulation program to calculate the system state points, and from which the system performance or fitness is evaluated. This process is repeated until the fitness of each string has been determined. It is at this point that the genetic algorithm is used to generate a new, improved population of strings.

The processes involved in the operation of the genetic algorithm are based on natural evolutionary processes of which the three most commonly used are reproduction, crossover and mutation.

Reproduction is an operator where a string is selected from the old or initial population and copied into the new population. As in Nature, the probability of a string being selected to pass its genetic material to the next generation depends on its fitness. Many strategies have been implemented for the reproduction operator and all seem to work provided that selection is biased towards fitness. The reproduction operator employed here determines the probability of selection for string i as:

$$P_{select} = \frac{f_i}{\sum f} \tag{4}$$

Where f_i is the fitness of string i, and Σf is the summation of all the fitness values for the entire population. In this way the new population will contain more copies of the fit strings, and fewer copies of the least fit strings.

Crossover is the second genetic operator which is used to create new, but related strings. Those strings selected for reproduction are grouped into pairs, an integer position k along the length of the string is randomly selected, and two new strings are created by swapping all bits between positions 1 and k. Figure 1 below shows crossover occurring at k = 5 for two strings A and B.

Before crossover

A	1	0	0	1	0	1	1	1	0	0	0	1
B	0	1	0	0	1	0	0	1	1	0	1	1

After crossover

A	0	1	0	0	1	1	1	1	0	0	0	1
B	1	0	0	1	0	0	0	1	1	0	1	1

Figure 1 Example of crossover operation on strings A and B

Crossover does not always occur for each pair of strings, and is controlled by the user defined probability, p_{xover}. If crossover does not occur then the offspring are exact copies of the two parents.

Mutation is the random changing of individual bits in the new population. The probability of mutation, p_{mutate} is set by the user and is typically of the order of 0.01. Thus with a population of 30 strings each 12 bits in length, only three to four bits would be expected to mutate in each generation. A mutation can create a novel bit pattern within a string which, if useful for improving fitness, will survive and flourish within future populations. If the probability of mutation is set too high it becomes a disruptive force, destroying too many useful bit patterns.

Verification of the genetic algorithm

The genetic search algorithm was programmed and first tested on a classical mathematical function used for testing optimizing schemes. The multimodal Shekel function (6) was selected for the test:

$$g = \frac{1}{(x_1-5)^2+(x_2-9)^2+0.5} - \frac{1}{(x_1-1)^2+(x_2-1)^2+0.1} - \frac{1}{(x_1-9)^2+(x_2-1)^2+0.025} \qquad (5)$$

This is a two dimensional function with two minima at coordinates (5,9) and (1,1) and the absolute minimum at (9,1) and the shape of this surface is shown in figure 2 . Here the chromosome only contains two parameters which map to the coordinates x_1 and x_2, of the equation The maximum and mean population fitness for each generation of the trial is shown in figure 3, and it can be seen that the genetic algorithm converges on the absolute minimum within 4 generations and ignores the local minima. On examination, the chromosomes having the maximum fitness contain the optimum values for the design parameters e.g. $x_1 = 9$ and $x_2 = 1$.

Discussion of the results

The genetic algorithm was used to optimize the design of the VAV air conditioning system using the following parameters:

Design Parameters

Coil contact factor	0.8	$< \beta <$	0.98
Room temperature	15	$< t_{ai} <$	25
Supply differential	8	$< \Delta t_s <$	12

Genetic Algorithm Parameters

Population size	N = 25
Probability of crossover	$p_{xover} = 0.7$
Probability of mutation	$p_{mutate} = 0.01$

Evaluation Parameters

	Scaling Factor, S_n	Weighting Factor, w_n
Volume flow rate, V_s	20	2
Coil duty, Q_c	320	1
Electrical power, Q_e	150	1

Figure 4 shows the values of maximum and mean population fitness for each generation as the search proceeds and the maximum population fitness is seen to converge on the optimum fitness of 0.611 within five generations. The actual numerical value of the fitness is of no practial interest, it serves only to indicate which of the 25 strings represents the best design; on decoding the fittest string, the actual numerical value of each design parameter may be found

That the GA had in fact found the true optimum was confirmed by an exhaustive search of all possible combinations of parameter values. For this example it required 4096 simulations and evaluations to be carried out and was only possible because of the high execution speed of the simplified mathematical model used. In contrast, the genetic algorithm found the optimum in five generations each with a population of 25 and therefore required only 25 x 5 = 125 simulations and evaluations: 3% of the time required for an exhaustive search.

Conclusions

Based on this preliminary study of genetic algorithms the following conclusions may be drawn:

(a) Genetic algorithms are a powerful optimisation tool and have already been successfully applied in a wide range of engineering applications.

(b) Genetic algorithms may be used to drive existing simulation software without modification to the source code.

(c) A genetic algorithm was used to optimize the performance of a VAV air conditioning system using a population size of 25, a probability of crossover of 0.7 and a probability of mutation of 0.01. The genetic algorithm successfully found the optimum combination of design parameters within five generations: 3% of the time necessary for an exhaustive search.

(d) Genetic algorithms appear to demonstrate considerable potential in the field of HVAC design, and further trials should be carried out on systems with constrained and discontinuous search spaces.

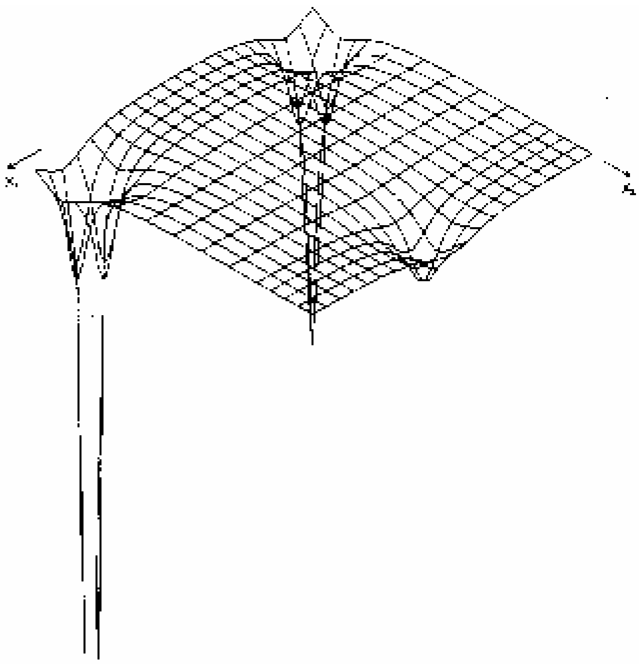

Figure 2 Shekel multimodal test function

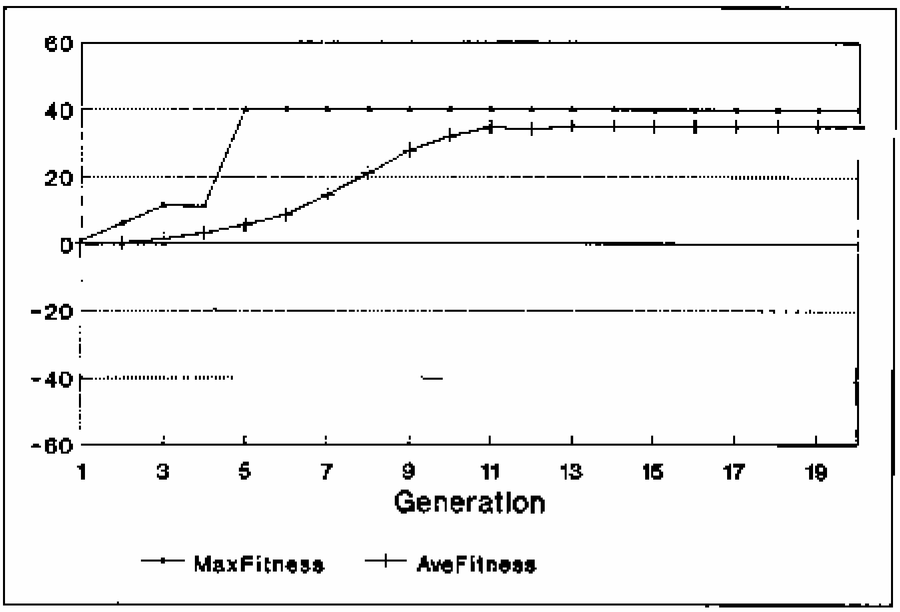

Figure 3 Result with genetic algorithm using multimodal test function

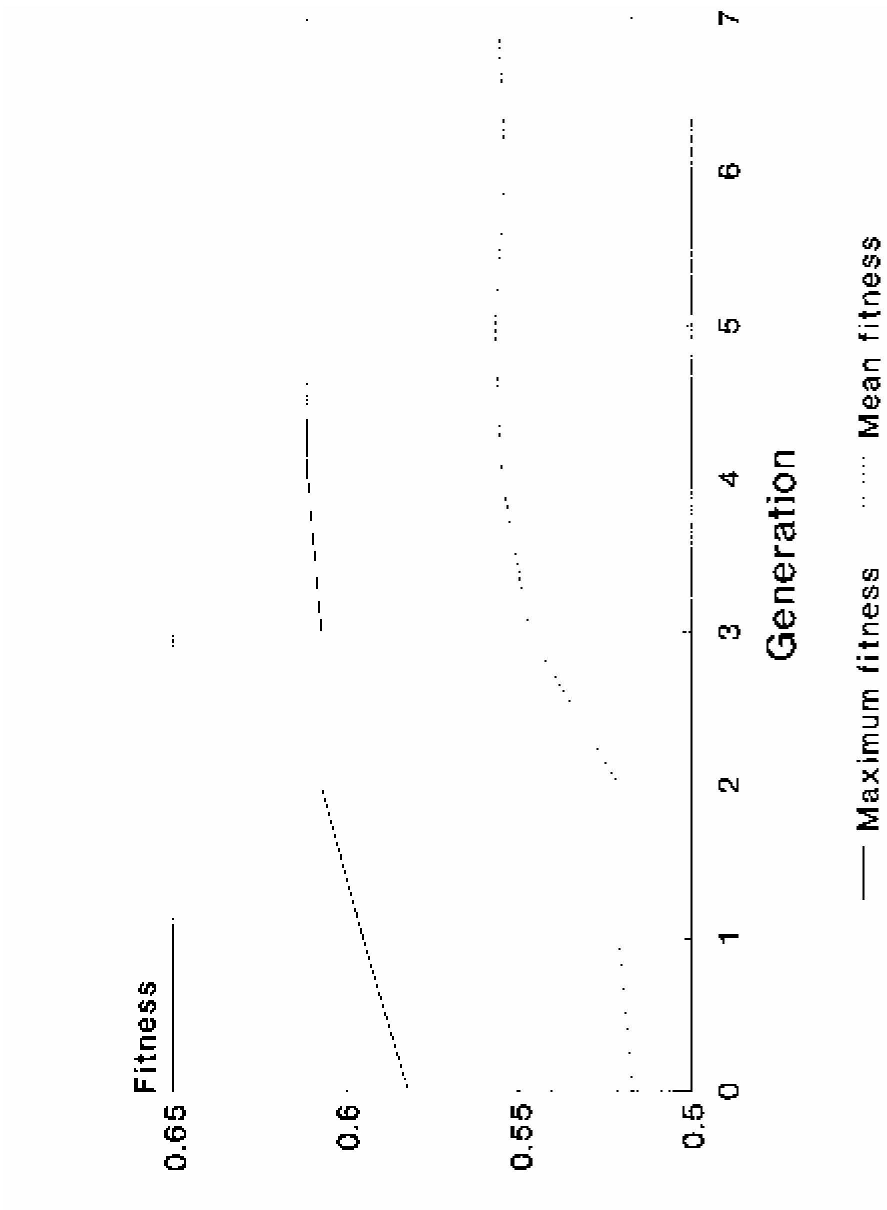

Figure 4   Result with genetic algorithm using VAV system simulation

References

1. Wright J A and Hanby V I: *The formulation, characteristics, and solution of HVAC system optimized design problems*; ASHRAE Transactions v93 Pt.2, pp.2133-2145, 1987.

2. Hanby V I and Wright J A: *HVAC optimisation studies: component modelling methodology*; Building Serv. Eng. Res. Technol. 10(1) pp.35-39 1989.

3. Holland J H: *Adaptation in natural and artificial systems*; Ann Arbor: The University of Michigan Press, 1975.

4. Goldberg D E and Kuo C H: *Genetic algorithms in pipeline optimization*; J. of Computing in Civil Engineering, ASCE v1 n2 pp.128-141 April 1987.

5. Goldberg D E and Samtani M P: *Engineering optimization via genetic algorithm*; Proceedings of the Ninth Conference in Electronic Computation, pp.471-482, 1986.

6. Gomez-Tierno M A: *Study on the use of the genetic algorithm for the solution of global optimization problems*; European Space Agency Contract No. 5377/83/D/JS/SC, Final Report, November 1985.

7. Kosak C, Marks J and Shieber S: *A parallel genetic algorithm for network-diagram layout*; Proceedings of the Fourth International Conference on Genetic Algorithms, University of California, San Diego, pp.458-465,1991.

8. Michalewicz Z and Janikow C Z: *Handling constraints in genetic algorithms*; Proceedings of the Fourth International Conference on Genetic Algorithms, University of California, San Diego, pp.151-157, 1991.

9. Janikow C Z and Michalewicz Z: *An experimental comparison of binary and floating point representations in genetic algorithms*; Proceedings of the Fourth International Conference on Genetic Algorithms, University of California, San Diego, pp.31-36, 1991.

Appendix 1 Mathematical Model of the VAV Air Conditioning System

The model used to predict the performance of the VAV air conditioning system comprised the following equations which describe the three psychrometric processes

<u>Mixing of recirculation and outdoor air</u>

$$t_m = x\, t_{ao} + (1 - x)\, t_{ai}$$
$$g_m = x\, g_m + (1 - x)\, g_{ai}$$

where the percentage of outdoor air, $x = m_{fa}/m_s$

<u>Cooling and Dehumidification</u>

$$t_c = t_m - \beta(t_m - t_{adp})$$
$$g_c = g_m - \beta(g_m - g_{adp})$$

<u>Room Supply</u>

$t_{ai} = t_c + \Delta t_s$
$g_{ai} = g_c + \Delta g_s$

where $\Delta t_s = \dfrac{Q}{m_s C_{pa}}$

$$\Delta g_s = \frac{Q_L}{m_s h_{fg}}$$

These equations, together with standard psychrometric equations, were solved using an iterative method and yield the values for temperature and moisture contents at each point in the system as well as the supply air mass flow rate.

The coil duty, Q_c was calculated from

$$Q_c = \dot{m}_s (h_m - h_c)$$

and the electrical energy consumption by the fan and refrigeration plant was calculated from

$$Q_E = \frac{m_s \rho \Delta p}{\eta_f} + \frac{Q_c}{COP}$$

The refrigeration plant coefficient of performance (COP) is a function of the coil apparatus dew point and was obtained by fitting manufacturers' data.

Nomenclature

C_{pa}	specific heat of humid air, kJ kg^{-1} k^{-1}
g	moisture content of air kg kg^{-1}
h_{fg}	latent heat of vaporication of water, kJ kg^{-1}
Q	Power, kW
t	temperature, ^{o}C
x	percentage of outdoor air, %
Δp	total fan pressure
Δg_s	supply moisture differential kg kg^{-1}
Δt_s	supply temperature differential, K
β	coil contact factor
ρ	density kg m^{-3}
η	fan efficiency (wire-to-air) %

Subscripts

adp	coil appratus dew point
ai	indoor air
C	coil outlet
fa	fresh (outdoor) air
L	latent
m	mixed air condition
s	sensible