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Overview of computational intelligence for building energy system design

Huajing Sha[a], Peng Xu[a,*], Zhiwei Yang[a], Yongbao Chen[a], Jixu Tang[b]

[a] Department of Mechanical and Energy Engineering, Tongji University, Shanghai 201804, China
[b] Aerospace Smart Energy Research Center, Shanghai 201804, China

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ABSTRACT

Building energy systems, i.e. heating, ventilation, and air-conditioning (HVAC) systems, are essential for modern buildings. They provide a comfortable and healthy indoor environment. Design quality has significant impact on HVAC system efficiency. The typical building energy system design process involving several procedures is repetitive and time-consuming. It is often limited by the engineer's experience, capabilities, and time constraints; thus, the design in most cases barely satisfies building codes. In recent decades, computational intelligence (CI) has achieved substantial improvements in various fields. This paper presents a comprehensive review of using CI for HVAC system optimization design. Firstly, this paper analyzes seven procedures which constitute a typical HAVC system design process and finds that optimization problems encountered during design process can be divided into three categories: model estimation, decision making and uncertainty analysis. Then a brief introduction of CI techniques used to solve HVAC design optimization problems and detailed literature review of application examples are given. Though the design problem varies with each other, this paper outlines a typical workflow which is able to solve most HVAC optimization design problems. At last, a framework of an integrated HVAC automation and optimization design tool is proposed. The framework is developed based on building information modeling (BIM) and extracted typical design optimization workflow. It is able to connect various design stages by implementing structured information transfer between them and ultimately improve design efficiency and quality.

1. Introduction

Building energy systems have been indispensable to providing a comfortable indoor environment in buildings. The energy consumed by heating, ventilation, and air-conditioning (HVAC) systems accounts for more than 40% of the total building energy consumption [1]. Whether a system is energy efficient or not is highly dependent on the system design quality. A typical HVAC design process contains seven procedures shown in Fig. 1. However, conventional HVAC system design practice is inefficient because a large amount of tedious and repetitive work (such as ductwork and piping) involved in the design process has to be solved manually [2]. On the other hand, complicated optimization analysis to improve system performance is merely done due to capability limitation of engineers. Scientists have put great efforts in finding methods to facilitate or even automate the HVAC design process for decades. In recent years, computational intelligence (CI) has gained great achievement in promoting the development of building industry such as automatic building space layout generation [3], efficient construction management [4] and building energy systems fault diagnosis [5]. CI is computational paradigms which are able to learning specific tasks from data or experimental observation [6]. Compared with the human's empirical practice and mindset, CI is more creative and productive in engineering design. Intelligent methods such as generative design and genetic algorithm are showing great potential in improving design efficiency and quality [7]. So more and more researches are trying to apply CI to facilitate and optimize HVAC design.

This paper is to provide a comprehensive overview of using CI techniques in the HVAC design process, provide practical advice on

Abbreviations: HVAC, Heating, ventilation, and air-conditioning; CI, Computational intelligence; AIA, American Institute of Architects; ASHRAE, American Society of Heating, Refrigerating and Air-Conditioning Engineers; GA, Genetic algorithm; ANN, Artificial neural network; BP, Back propagation; MLR, Multiple linear regression; ELM, Extreme learning machine; RC, Resistor–capacitor; MIGA, Multi-island genetic algorithm; DP, Dynamic programming; AI, Artificial intelligence; TETD, Total equivalent temperature difference; CLTD, Cooling load temperature difference; KBES, Knowledge-based expert system; LCC, Life-cycle cost; VAV, Variable air volume; GLR, Global load ratio; SLR, System load ratio; ZLR, Zone load ratio; AHU, Air handling unit; DSM, Downhill simplex method; MBD, Model-based design; STM, Simplified thermal models; PV, Photovoltaic; BIM, Building information model

* Corresponding author.
E-mail address: xupeng@tongji.edu.cn (P. Xu).

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Nomenclature

k	Stage
x_k	State at stage k
$u_k(x_k)$	Action taken at State x_k
T_k	State transition rule
p_{0n}	Policy from stage 0 to n
$v_k(x_k, u_k)$	Objective function at State x_k taking the action u_k
$V_{kn}(x_k, x_{k+1}, ..., x_n)$	Objective function from stage k to n
$f_k(x_k)$	Optimal objective when taking optimal action u_k^* at stage k
$(loads_{sens\_Pd})_{zone}$	Zone level sensible peak load (W)
$(loads_{sens\_Pd})_{system}$	System level sensible peak load (W)
$hours_{oper\_syst\_Pd}$	Number of system operating hours
$(loads_{sens\_Pd})_{syst\_at\_hour\_i}$	System level sensible peak load at the ith hour (W)
$(loads_{sens\_Pd})_{build\_at\_hour\_i}$	Building level sensible peak load at the ith hour (W)
$F(x)$	Objective function
$f_i(x)$	The ith sub-objective function

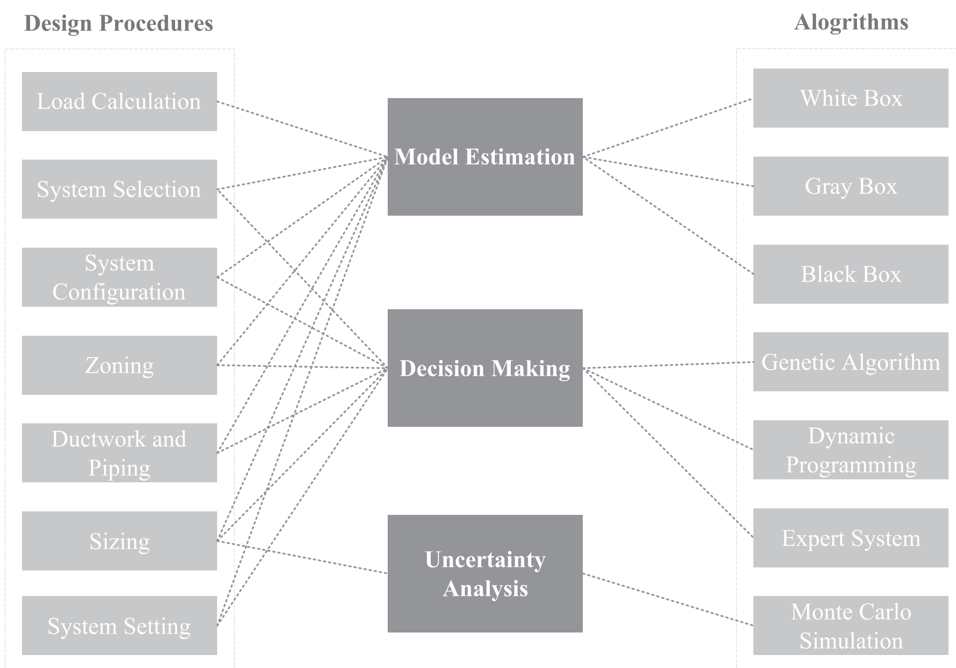

Fig. 1. HVAC design problem classification and algorithms.

how to conduct optimization design to improve building HVAC system performance. Also, this paper proposes an integrated design framework which may provide inspiration to researches working in this field. This paper is organized as follows. Section 2 briefly describes the methodology applied by this review paper. Section 3 analyzes seven HVAC design procedures, categorizes them into three types of optimization problems. Section 4 introduces the most commonly used CI techniques of solving HVAC optimization problems. In Section 5, explanation of each design problem and literature review of corresponding application examples of intelligent techniques are presented. Section 6 summarizes the approaches used to solve design optimization problems and then extracts typical workflow of HVAC design optimization. Also, Weakness of current methods is pointed out in this Section. Based on the above review and analysis, the framework of an integrated HVAC optimization design tool is proposed. This framework is developed based on building information modeling (BIM) and the extracted typical design optimization workflow. It is able to automatically connect design stages by implementing structured information transfer between them. In the last section, main findings and contributions of this paper is summarized.

2. Methodology

This review is conducted based on: (a) searching databases of journal, conference articles and books, (b) information from specific professional websites and (c) experience in the implementation of HVAC optimization design. The literature search is carried out using keywords including two categories: (a) computational intelligence techniques (i.e. genetic algorithm, neural networks etc.), (b) application (i.e. HVAC system design, optimization etc.). The keywords are combined using "OR" and "AND" to conduct comprehensive searching in several popular search engines including IEEE Xplore (http://ieeexplore.ieee.org/Xplore/home.jsp), ScienceDirect (http://www.sciencedirect.com), EI Compendex (https://www.engineeringvillage.com) and Google Scholar (http://scholar.google.co.uk). Cited articles are all included in this paper.

3. HVAC optimization design problems

A typical HVAC design process containing three stages is defined by the American Institute of Architects (AIA) [8]:

1. Schematic or conceptual design. In this phase, designers need to figure out the appropriate system type and configuration according to building features and local resources.
2. Design development. In this phase, HVAC engineers produce detailed design documents including layouts, equipment schedules, and construction details.
3. Construction design. In this phase, detailed construction drawings and specifications are produced.

For real engineering practice, the HVAC design process is further

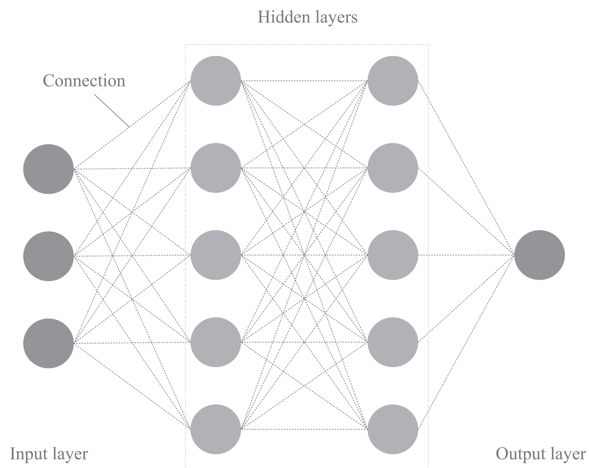

Fig. 2. Typical structure of ANN.

refined into seven procedures listed in Fig. 1 (left column). In this paper, how to complete each design procedure is defined as a 'design problem'. However, solving HVAC design problems in line with empirical practice or mandatory building codes does not guarantee an efficient system. So more researchers are now applying CI to conduct HVAC system design optimization for better system performance. According to Dickinson and Bradshaw [9], the HVAC design optimization problems can be classified into two classes. The first one is the optimization of static design parameters. The static parameters are the ones that determine the physical appearance of the system, such as zoning, system components and plants, and duct layout. These parameters will not change after the HVAC system has been constructed. The second one is the optimization of dynamic input variables, for example, operation schedule and control setpoints. These input variables can be adjusted throughout the system life cycle. The first six design procedures fall into the first class, whereas the system setting belongs to the second one.

According to the characteristic of optimization design problems, they are classified into three categories in this study: model estimation, decision making, and uncertainty analysis. The model estimation provides a mathematical representation of the target problem, which can be used to evaluate the physical features of a solution. Load calculation belongs to the category of model estimation because it can be taken as a problem to find the physical feature of a building and present it using a series of values called "load." For the problem of decision making, the objective is to find the optimal design parameters or solutions subject to constraints and boundary conditions. During the iterative process of decision making, a model has to be established to evaluate the fitness of a solution. Thus, model estimation and decision making are closely related. Three decision-making algorithms are discussed in this paper. The first two (i.e., genetic algorithm (GA) and dynamic programming) are based on mathematical derivations whereas the expert system is largely dependent on expert experience. Uncertainty analysis aims to investigate the influence on system performance by variables that have inherent uncertainties, such as weather condition and occupancy schedule. Another aim is to improve the reliability of a decision through the quantification of uncertainties. The right column of Fig. 1 lists the algorithms that are most widely adopted to solve HVAC optimization design problems. In the following sections, brief introduction of each algorithm and literature review of optimization design examples are provided.

4. CI algorithms for HVAC optimization design

4.1. White box method

In the white box method, a series of mathematical models are built based on physical prior knowledge of energy–mass balance, heat transfer, momentum, and flow balance. Thus, it is also called physical-based modeling. The models are usually built up stepwise, starting from very simple physical relationships. Each equation of a white model is physically meaningful. The white box method is commonly used in the HVAC industry. Examples of physical-based models include chillers [10–12], cooling towers, zones [13,14], mixing boxes [15], heating/cooling coils [16–18], fans or pumps [14], sensors [13], and dampers [14]. The commonly used energy simulation tool is also a white box model. In contrast to previous simple models of a specific component or unit, the whole building simulation tool is an integrated model, which is capable of calculating the energy required for heating, cooling, ventilation, and lighting equipment in a building.

4.2. Black box method

The black box model is often called a data-driven model. It is developed based on large amounts of data collected from experiment or real world. It uses statistical techniques to capture the mechanism behind the data, without being explicitly programmed. A data-driven model is especially suitable for tasks where the design and programming explicit algorithms are difficult or impossible. It is also gaining increasing attention in the building industry such as building design [20], energy prediction [23,24], and fault detection of HVAC systems [25,26]. The most commonly used data-driven model included in this research is artificial neural network (ANN). ANN is inspired by biological neural networks that constitute animal brains. An ANN is composed of a collection of connected units or nodes called artificial neurons. Each connection can transmit a signal from one artificial neuron to another. The connections between artificial neurons are called "edges." Neurons and edges typically have a weight that adjusts as the learning proceeds. A typical neural network structure is shown in Fig. 2. Each circular node stands for an artificial neuron. Nodes in input and output layer represents input and output variables respectively. While neurons in hidden layers perform activation and transformation to input signals. Once the structure is determined, the weights and parameters can be trained through a back propagation (BP) algorithm. Therefore, it is sometimes called a BP network.

In addition, multiple linear regression (MLR) and extreme learning machine (ELM) are also adopted to estimate building loads. ELM is a modification of the single-layer feedforward network for classification, regression, and clustering [27]. It can be obtained by removing BP from a multilayer perceptron. The parameters of hidden nodes can be randomly assigned and never updated or inherited from ancestors without being changed. Thus, ELM can produce a good generalization performance and learn much faster than models such as ANN.

4.3. Gy box method

The gray box model is a hybrid model that takes advantage of both the white box model and black box model. The whole framework of the gray box model is based on physical rules while some model parameters are determined using data-driven methods. The resistor–capacitor (RC) network is a commonly used gray model for estimating air-conditioning loads. It uses an analogy to the electrical circuit to model heat transfer through structures.

4.4. Genetic algorithm

GA is a metaheuristic inspired by the process of natural selection. It is a popular method to generate high quality solutions to optimization and search problems in the building industry [19,20]. The design of HVAC systems generally involves the selection from among a number of alternatives with specific constraints to ensure that the system can provide the desired performance [21]. An engineer rarely has time to search for the global optimum and usually adopts a solution complying with the rule of thumb. GA is easily illustrated by the metaphor of natural evolution. A set of individuals (usually represented by points within the search space) is randomly initialized and then the individuals evolve; the ones with the highest fitness have the highest probability of surviving. The individual is an alternative solution with several properties represented by chromosomes (often in the format of binary strings). The chromosomes can be muted and altered with certain operators. GA has two evolution operators: crossover and mutation. Crossover, which is inspired by nature, involves changing two randomly chosen chromosomes to create a new individual called offspring. The mutation operator involves generating modifications on an allele to maintain genetic diversity. It is analogous to biological mutation. Then, the selection of an individual is conducted by a cost/fitness function that measures its performance. The solution with the highest fitness will most possibly be selected for the next generation. The structure of a single population GA is illustrated in Fig. 3. A simple GA can easily fall into a local optimum; thus, several adaptive GAs are developed for better performance such as multi-island GA (MIGA) [69], nondominated sorting GA (NSGA-II), multiobjective GA [22], and GA with refined process [86].

4.5. Dynamic programming

Dynamic programming (DP) is a mathematical decision-making method developed by Richard Bellman in the 1950s [28]. It has found application in numerous fields, from engineering to economics. DP is a very general solution method for problems that have two properties: (i) optimal substructure and (ii) overlapping subproblems. It breaks a complex problem into several stages based on time or spatially dependent features. The final solution is composed of the optimal solution of each subproblem. It possesses the following characteristic: "Regardless of the initial conditions and initial decisions, the future condition and decision resulting from these initial conditions and decisions must be able to produce the best solution for the problem."

There are several key concepts of DP [29]:

(1) Stage, denoted as k. A complex problem is divided into several stages. Each stage is related to each other temporally or spatially. The number of stages could be finite or infinite depending on the target problem.
(2) State, denoted as x_k. A state represents the situation of the current stage. It captures all relevant information from the history. In other words, the state should be defined to be a sufficient statistic of the future. The state variable could be a single value or a vector.
(3) Action, denoted as $u_k(x_k)$. It is a decision made in state k.
(4) State transition rule, denoted as T_k. When an action is taken in stage k, the state transition rule determines the state of stage $k+1$. That is,

$$x_{k+1} = T_k(x_k, u_k) \tag{1}$$

(5) Policy, denoted as p_{0n}. It is formulated by a series of actions from stage 0 to n.

$$p_{0n}(x_0) = \{u_0(x_0), u_1(x_1), \ldots, u_{n-1}(x_{n-1})\}. \tag{2}$$

(6) Objective function, denoted as $v_k(x_k, u_k)$. It is the reward resulting from taking action u_k at stage k. The objective function from stage k to n is denoted as $V_{kn}(x_k, x_{k+1}, \ldots, x_n)$. It is the combination of reward from stage k to n.

$$V_{kn}(x_k, x_{k+1} \ldots x_n) = \sum_{i=k}^{n-1} v_i(x_i, u_i) \tag{3}$$

The process of DP could be described by the following equations:

$$\begin{cases} f_k(x_k) = opt\{v_k(x_k, u_k) + f_{k+1}[T_k(x_k, u_k)]\} \\ \qquad = v_k(x_k, u_k^*) + f_{k+1}[T_k(x_k, u_k^*)] \\ \qquad k = n-1, n-2, \ldots, 3, 2, 1, 0 \\ \qquad\qquad f_n(x_n) = 0 \end{cases} \tag{4}$$

where $f_k(x_k)$ is the optimal objective when taking optimal action u_k^* at stage k.

4.6. Expert system

An expert system is an interactive computer program that captures and encodes the specific knowledge of a particular domain. It emulates the decision-making process of a human expert using if-then rules rather than conventional procedural codes. The system has been successfully used in areas such as prediction [30], diagnosis [31], planning [32], and control [33]. It is deemed as one of the first truly successful forms of artificial intelligence (AI) software [34]. Such system highly depends on domain knowledge. It consists of two subsystems: inference

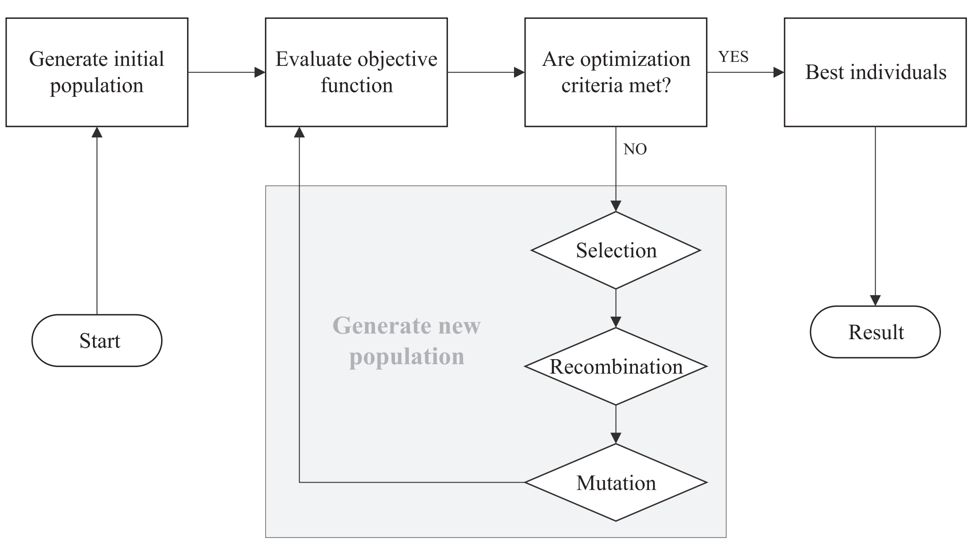

Fig. 3. Structure of a single population genetic algorithm.

Table 1
Information summary of black box models for building load/energy estimation.

Ref.	Input features	Output	Model Type	Research Objective
[47]	Wall to floor ratio, window to wall ratio, occupancy, wattage of lamps per unit area and wattage of equipment, indoor design dry-bulb temperature	Cooling load index (W/m^2)	ANN 6-x-1[a]	Predict the maximum possible load of a building with high efficiency and accuracy
[48]	Areas of windows, walls, partitions and floors; type of windows and walls; classification on whether the space has roof or ceiling; design room temperature	Heating load (W/m^2)	ANN 6-10-10-1	Learn to predict the required heating load of different types of buildings with minimum input data
[49]	Mean indoor air temperature, mean radiant temperature, relative humidity, carbon dioxide concentration, mean illuminance, lighting and equipment energy, dry-bulb air temperature, relative humidity, rain depth, wind speed	Hourly energy consumption (kWh)	ANN 10-20-20-1	Use a few parameters such as illuminance as proxy variables, combined with weather data, to predict hourly energy consumption
[50]	Value of seasons, insulation, masonry thickness, constant or variable heat transfer coefficient	Annual heating energy consumption (kWh)	ANN 5-23-23-1	Generate a mapping between wall property and heating energy for a passive solar building
[51]	Width/length ratio, wall overall heat transfer coefficient, area/volume ratio, total external surface area, total window area/total external surface area	Heating load (kW/m^2)	ANN 4-7-5-1	Predict heating load of existing buildings benefiting from geometry, construction, layout, climate, and users by using ANNs and compare the results with a building energy simulation tool called KEP-IYTE-ESS
[52]	Total building area, number of stories, depth, aspect ratio, orientation, roof R value, roof color, roof emissivity, window U value, window SHGC, wall U value shading, projection factor, window-to-wall ratio	Annual energy consumption (kWh)	LR	Develop an assessment tool to provide rapid feedback based on changes in high-level design parameters for architects in the early design stage
[53]	Orientation, insulation thickness, window-to-wall ratio	Heating energy (Wh)	ANN 3-20-1	Provide a quick estimating tool for building envelope design during early design stage
[54]	Building orientation, top floor batt insulation, ceiling interior finish, ceiling insulation, floor construction, top floor ceiling exterior insulation, top floor ceiling interior finish, etc. (17 parameters in total)	Annual energy consumption (kWh)	MLR	Build a fast energy estimating model for office buildings in five different climate regions in the U.S.
[55]	Relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, glazing area distribution	Heating/cooling load (kW)	ELM	Explore different machine learning techniques for estimating the heating load and cooling load of residential buildings
[56]	Shape of building, relative compactness, glazing area, roof area, surface area, wall area, orientation, overall height, glazing area distribution	Heating/cooling load (kW)	ELM	Explore the dataset and features correlating to building load and their association strength

[a] This represents the structure of an ANN. The first and last integer indicate the number of input and output variables. The inside integers represent the number of neurons in each hidden layer. For example, 6-10-10-1 means that there are six variables in the input layer and one variable in the output layer. The two hidden layers contain 10 neurons respectively. x means that details of the ANN structure is not provided in this study.

engine and knowledge base. The inference engine acts as the logic decision maker to deduce results according to outside conditions. The knowledge base contains the facts and rules as the reference for reasoning. Ease of maintenance is the most obvious benefit of expert systems. In conventional computer programming, the logic reasoning process is synthesized into a code and is difficult to understand. With an expert system, the knowledge base is intuitive and easily understood, reviewed, and even edited by a domain expert rather than an IT expert. The main disadvantage of expert systems is the difficulty in knowledge acquisition, representation, and processing. Early expert systems were built using executed interpreted (rather than compiled) codes. Interpreting is easily understood and evolved but it is impossible to match the efficiency of the fastest compiled languages, such as C [38].

4.7. Monte Carlo simulation

Monte Carlo simulation is a computational algorithm that relies on repeated sampling to obtain numerical results. The essential idea is to solve problems that are deterministic in principle through randomness. It is a technique used to understand the impact of risks and uncertainties in prediction and forecasting models. It has now found wide applications in various fields, such as finance, project management, energy, manufacturing, and engineering. The Monte Carlo simulation performs risk analyzes by building models of possible results through substituting a probability distribution for any factor that has an inherent uncertainty. It produces distributions of possible outcome values through thousands of recalculations. For risk analysis, probability distributions are a much more realistic way of describing uncertainties than a single value.

The Monte Carlo simulation is usually conducted with three steps: sampling, simulation, and statistical analysis. There are three widely used sampling methods: random sampling, stratified sampling, and Latin hypercube sampling [35–37]. In the random sampling method, a sample is randomly selected from the entire sample space at each time. The process needs to repeat N times if N samples are required. One problem of random sampling is that it cannot represent the entire population unless the sample size is large enough. In the stratified sampling method, the sampling space is first separated into I disjoint sections. J samples are selected randomly from each section. However, it is time-consuming in the separation process. In the Latin hypercube sampling method, a near-random sample of parameter values is generated from a multidimensional distribution. When sampling a function of N variables, the range of each variable is divided into M equally probable intervals. M^N sample points are placed to satisfy the Latin hypercube requirements. Each sample is the only one in each axis-aligned hyperplane containing it. With the same sample size, the Latin hypercube sampling provides much more reliable representation of the population than random sampling [37].

5. Literature review of HVAC intelligent design

5.1. Load calculation

The ultimate function of the HVAC system is to handle the building load to keep the building indoor environment comfortable. Building heat gain is the synthesis effect of several components including both instant solar radiation and delayed release of radiation, heat transfer through the envelope, and internal heat produced by humans, lighting, and electrical equipment. It is a dynamic process following the pattern of building usage schedules and weather condition. A precise estimation of building load is essential for the system design and component sizing. Several load calculation methods have been developed such as total equivalent temperature difference (TETD), cooling load temperature difference (CLTD), transfer function method, heat balance, and radiant time series [39]. TETD and CLTD can be used to estimate the peak load, which is not sufficient for HVAC design. With the development of computers, automated building load calculation programs have been developed.

Simulation programs such as EnergyPlus [40], eQuest [41], ESP-r [42], IBPT [43], SIMBAD [44], and TRNSYS [45] are widely used for building load calculation and energy analysis in the past decades. These simulation programs were developed based on physical principles and detailed input information. The following capabilities are commonly available in an energy simulation tool: heating/cooling load calculation considering conduction, convection, long wave and short wave radiation; ventilation calculation with multiple zone airflow networks; HVAC system performance integrating plants, distribution systems, and terminals; and tight coupling between instantaneous building load and HVAC system performance [18]. Crawley et al. [46] made a comparison of the features and capabilities of 20 major building simulation programs. Load estimation accuracy is greatly improved with the help of these programs. However, it is time-consuming to perform load estimation using simulation tools because physical models have to be established and hundreds of input parameters are required for the calculation procedure.

Data-driven models ignore the physical principle of thermal transfer and use a large amount data to figure out the underlying mechanism. ANN is most widely used to build the black box. The success of ANNs depends on five distinctive features: learning, self-adaptive, fault tolerance, flexibility, and real time response [49]. Besides, ANN is especially suitable for managing complex nonlinear problems. The data usually coming from simulation tools or energy survey are split into training set and test set. Training data are used to build the network and find proper weighting factors while test data are used to measure the accuracy. Table 1 lists the developed data-driven models for load estimation. It should be noted that the load estimation discussed here is different from the load prediction that uses previous data to infer the load for the next few days or months. Among the three methods discussed here, ANN and ELM are capable of representing the nonlinear relationships between input and output parameters while MLR cannot. Numerous input variables are required for MLR to establish the load estimation model in [51]. Besides, different models are built respectively for each climate zone because the complicated relationship between weather and energy consumption cannot be mapped by a linear model. From this viewpoint, the linear regression model is less accurate for load estimation than the other two methods.

Gray models assume the physical structure and parameters with definite physical meaning. The RC thermal network is a widely used gray model for thermal delays caused by a building envelope and internal thermal mass effects. Later on, a modified RC model was developed. Seem et al. [57,58] proved that 3R2C was especially suitable for calculating heat transfer through external building envelopes. The 2R2C model took the building internal mass (e.g., internal structure, partitions, carpet, and furniture) into consideration [60]. It was represented by a lumped thermal internal mass. More recent version of RC models are 3R4C and 4R5C developed by Fraisse [59].

5.2. System selection

System selection is conducted in the early design phase. Numerous choices of HVAC systems are available for a given building. Conventionally, system selection is based on factors such as building functions and weather condition. A suitable system selection is critical for achieving high overall building performance. However, it is often limited by the engineer's experience, capabilities, and time constraints, resulting in suboptimum system selection. Expert systems and GA have been adopted by researchers to solve this problem.

In the construction industry, a successful system design depends on the engineer's knowledge and experience. Therefore, the knowledge-based expert system (KBES) [61] was once a popular methodology to help determine the appropriate HVAC system during the conceptual stage. An expert system called Select-HVAC was developed by Fazio et al. [61]. It was used as an advisor, helping designers to configure and size the HVAC equipment for different locations worldwide in terms of indoor requirements and outdoor and indoor air pollution. Ballal [62] developed a software package of expert system that provides guidelines for selecting equipment for air-conditioning systems in an interactive manner for any space located in India. Maor et al. [63] proposed a general framework of KBES, which was capable of automatically synthesizing the complete set of possible HVAC systems. This synthesis was performed through two levels. Level 1 started with all possible primary systems (or secondary systems) and used static expert knowledge to generate the permissible design alternatives of secondary systems (or primary systems). Level 2 used dynamic application knowledge including intuition rules and matching rules to combine the secondary systems among themselves with primary systems. ANSI/ASHRAE/IESNA Standard 90.1-2001 was used to set the minimum allowable energy performance for choosing equipment. A companion paper was published later to demonstrate their methodology through an office building [64]. In an ASHRAE research project, Shams et al. assembled, developed, and verified a knowledge base for the selection of HVAC system types for small office buildings (less than 20,000 ft^2) in two climatic regions: cold and hot/humid. This project included the selection of primary energy and distribution system types. A knowledge-based system was developed [65,66]. With regard to primary energy system, Case et al. [67] also created an expert system shell specifically designed to address the task of designing thermal energy systems for buildings.

Janghoo et al. [69] proposed an optimal design method for an HVAC system using a modified GA called MIGA. This algorithm was able to avoid converging to a partial optimal solution, which can easily occur in a simple GA. Their research used TRNSYS to calculate the cooling and heating loads. The analysis result was used to select the type and capacity of the equipment system that could minimize energy consumption. Bichiou et al. [70] developed a comprehensive simulation environment for selecting an optimal HVAC system type and the best combinations of building envelope and HVAC system features in residential buildings. GA was one of the three optimization algorithms considered in this simulation environment. Life-cycle cost (LCC) was used as the cost function to perform optimization. LCC contained both initial cost and annual energy cost with the constraints of maintaining acceptable thermal comfort. Annual cost was calculated with the whole building simulation tool: DOE-2. Fourteen alternative HVAC systems (including AC with furnace and AC with electric resistance) formed the search space. This research also did a case study showing that it was possible to design and operate a house with an annual total energy cost of less than US$1000 in Boulder, CO; Chicago, IL; and Phoenix, AZ.

5.3. Zoning

Zoning of HVAC systems is determined through a delicate balance between first cost and comfort. Ideally, each room or workspace should be treated as one zone. Actually, in real design practice, rooms with similar functions are often grouped into one zone to save budget. For the sake of operating convenience and energy savings, the design criterion states that rooms with different conditioning requirements, functions, load features, or large distances are better served by separate subsystems. This criterion differs from the conventional zoning strategy, and GA is often used to find the optimum solution with massive calculation.

The research done by Stanescu et al. [68] discussed an optimal zoning strategy for HVAC system design. A GA combined with whole building simulation software to evaluate the HVAC energy consumption was proposed. The variables selected for optimization were the grouping of zones served by the system and number of systems serving the building. The HVAC system type in this research was specific to a variable air volume (VAV) system. At first, variables (i.e., number of systems and grouping of zones) were randomly initialized as the first generation for optimization. The candidate solution used a permutation representation as a set of integers. The length of the permutation vector was the number of zones, each of which occurs once. Zones were randomly placed in the vector and randomly selected break points were used to group zones into systems. At each step, the evolved generation was evaluated by the DOE-2 model to calculate the objective function until the predefined condition was met. Three types of operators (i.e., mutation, mutation and crossover, and crossover) were analyzed in this research. The HVAC energy consumption savings ranged from 22.7% to 25%, compared to the reference building. However, it required two to four days to complete the computation because thousands of simulations were performed using DOE-2. In their later research [71], a simplified method was presented to evaluate the fitness of each alternative solution. They proposed the idea of global load ratio (GLR), system load ratio (SLR), and zone load ratio (ZLR) and found that GLR was closely related to the HVAC energy consumption. The higher the GLR, the lower the energy consumption. In the new optimization procedure, the HVAC energy consumption calculation using a detailed DOE-2 model of the building was no longer required. Computing time had been significantly reduced with this simplified method and its accuracy approximated that of the detailed simulation method.

$$ZLR = \sum\nolimits_{i=1h}^{24h} (loads^{i}_{sens\_Pd})_{zone\_at\_hour\_i} / Max(loads_{sens\_Pd})_{zone} * hours_{oper\_syst\_Pd} \tag{5}$$

$$SLR = \sum\nolimits_{i=1h}^{24h} (loads^{i}_{sens\_Pd})_{syst\_at\_hour\_i} / Max(loads_{sens\_Pd})_{syst} * hours_{oper\_syst\_Pd} \tag{6}$$

$$GLR = \sum\nolimits_{syst=1}^{n} \left(SLR \bullet \sum_{1h}^{24h} (loads_{sens\_Pd})_{syst\_at\_hour\_i} / \sum_{1h}^{24h} (loads_{sens\_Pd})_{build\_at\_hour\_i} \right) \tag{7}$$

Berquist et al. [72] also used GA for determining the zoning strategy. Different from the mono-criteria optimization conducted by Stanescu et al. [68,71], this research adopted multiple criteria (i.e., initial cost, system efficiency, and occupant comfort), and user-defined weighting factor for each criterion was allowed to comply with the current industry practice. They also performed a mathematical analysis using Matlab coding to compare the energy consumption and days that the room temperature exceeds the setpoint for different strategies. Various supplier VAV specifications were found online and incorporated into the code.

5.4. Sizing

Proper sizing of system components (i.e., chiller, pump, air handling unit (AHU), etc.) is very important for an efficient HVAC system operation. Oversized systems operate away from the nominal conditions and result in low efficiency, while undersized systems cannot meet the building cooling or heating demand. The conventional sizing method is based on the calculated peak load combined with some safety factors. However, building loads rarely reach peak design values and plants normally operate under partial load conditions. Therefore, research was conducted attempting to optimize the system configuration. Djunaedy [73] listed the signature and penalties of an oversized system with an example of a rooftop unit. Lee et al. [74] developed a simplified model for evaluating the performance of a chiller system considering the number and capacity of chillers. It was claimed to be a convenient tool for designers to quantify the trade-offs between energy efficiency and other factors.

GA, as one of the most popular optimization algorithms, is also used for HVAC system sizing. Wright and Farmani [75] developed a GA-based method for simultaneous optimization of building fabric construction, HVAC system, and plant control strategy. The system was a single-zone all-outside air system and the air treatment component to be optimized included coil height, coil width, water circuit, and fan size. The objective function was the operational cost. In his later research, a multiobjective GA method was used to search for the optimum pay-off characteristic between the energy cost and occupant thermal comfort. The optimum pay-off characteristic was represented by a Pareto set of solutions and GA was used as a search method to find the optimal solution. This research was conducted on the same system as his previous one [76].

The design parameters such as weather condition, internal load, and building physics come from statistical data regardless of actual condition. Because the actual heating and cooling demands required to size the system are always uncertain, an uncertainty analysis of HVAC system sizing becomes a research hotspot. Building performance is assessed under multiple possible conditions by which the determination is based.

Huang et al. [77] proposed a method for HVAC system sizing concerning peak load uncertainty and multiple-criteria decision making. The conventional sizing method for components is based on a deterministic peak load, which is predicted from typical weather conditions and a safety factor. The systems are always oversized. In their research, they performed a Monte Carlo simulation to obtain the statistical distribution of peak load and corresponding energy consumption and failure time. Combined with preference factors assigned by customers, a simple multi-attribute rating technique was used to make the final decision. They also proposed a strategy to optimize the configuration of multiple-chiller plants taking into consideration the load side uncertainty and the COP uncertainty through a life-cycle analysis [78]. Sun et al. [79] explored a new framework to guide the use of uncertainty analysis and sensitivity analysis in HVAC system sizing. Instead of conducting a deterministic calculation procedure after collecting input data, a series of analysis including uncertainty quantification, dynamic simulation, and probabilistic prediction of interested index was performed to determine the quantifiable margins based on the desired level of system performance guarantees. The uncertainty quantification was specific to the parameters of weather, building envelope, material, and operation. A Monte Carlo based simulation was used to sample the variables. Kang et al. [80] developed a sizing method taking into consideration the scenario parameter uncertainty and the discrete spectrum of nominal cooling capacity of chillers. This approach revealed the impacts of scenario uncertainty on peak cooling load, chiller LCC, and annual unmet hours based on Monte Carlo method and dynamic simulation.

5.5. Configuration

Configuration refers to the integration of HVAC components to form a system. Wright and Zhang et al. [81–84] developed a model-based optimization procedure for the synthesis of a novel HVAC system configuration using GA. Three suboptimization problems were considered in their research: the choice of component set, the design of topological connections between components, and the system optimal operation strategy design. Minimizing energy consumption was the optimization objective of this research. This configuration synthesis was a multi-level optimization problem. The topology optimization depends on component selection, whereas the control strategy design changes with the different components and topology. A simultaneous evolutionary approach was adopted to solve this problem. All optimization variables of the configuration have been encoded into an integrated genotypic data structure. Once a configuration solution was developed, the optimal control setpoints had to be optimized to assess the performance of this configuration solution. In this research, a new evolutionary algorithm operator named “Aging” was developed to solve the problem of a single topology dominance due to the highly constrained nature of this optimization problem [85]. The optimal synthesized system developed by this method was judged by comparing with the performance of three benchmark systems. The result showed that the best of the synthesized system had a capacity that was also close to the minimum possible capacity and its performance exceeded that of the conventional system and was comparable to that of a conceptually optimum system configuration.

5.6. Ductwork and piping

One of the most energy consuming and costly components of an HVAC system is the fluid distribution system [87]. The main objective of distribution system design is to provide the required fluid flow rate at adequate pressure to each terminal demand point. Energy is required to distribute fluid and overcome all pressure losses of various components in the ducting system (e.g., fittings and dampers). The design procedure of ducting system can be divided into three stages. First, the ductwork layout needs to be determined. Then, the duct material and size and fans are selected; finally, dampers for each branch are calculated to balance the system.

For conventional duct network design, heuristics-based methods without optimization are often used. Assumptions for variables such as airflow rate and friction losses are based on design experience [88]. The most commonly used methods are equal friction and static regain method [39]. For computer-aided optimal duct design, the main goal is to determine optimal duct sizes that could minimize LCCs. The most widely known method is the T-method developed by Tsal and Chechik [90,91]. This method used the idea of DP. It can determine optimal duct sizes by optimum distribution of pressure throughout the system in order to minimize LCC, which includes initial ductwork cost and year-round energy consumption of the fan. Three major procedures were incorporated in the method: system condensing, air-handling unit selection, and system expansion. The T-method had been recommended by the ASHRAE handbook for routine design practice. Although the T-method was criticized for its shortcomings such as complex computation procedure, poor control of flow velocity and duct diameter [92], and inapplicability to duct systems with multiple fans [93] it was the first to introduce the idea of LCC for duct optimal design, where further modified optimal methods were based.

Ting et al. [93] proposed a DP method, which considered the system pressure equilibrium and least LCC, to derive the duct size and fan capacity. The design process was divided into several stages each of which was represented by a state vector comprising a set of state variables describing the system condition such as the pressure value of the duct. It used DP to obtain the optimal solution. Compared with the T-method, DP produced a smaller duct area, and therefore, the initial cost would be lower. Moon et al. [92] developed a modified T-method, which could analyze the flow distribution for a multiple fan duct system, and a bathroom ventilation system in a 20-story residential building was selected as an example application.

Apart from the above DP-based optimal duct design methods, GA is also a popular method for duct optimal design. The optimization objective is also the LCC. Asiedu et al. [94] proposed a GA-based duct design method with a minimum LCC. It incorporated standard discrete duct sizes, variable hourly operating conditions, and utility rates into the design process with the constraints of pressure balancing and size/flow limitations. Narváez et al. [95,96] used the GA method to determine the optimal tube and pump size of hydraulic system taking into consideration minimization of costs and constraints of velocity, flow, and pressure. Each chromosome was a representation of the fluid transportation system codified with two chains of whole numbers, where the first part was the diameter of each pipe and the second one was the pumping equipment. The individual was adjusted to minimize the cost function representing the LCCs.

DP and GA are relatively complicated to implement and require costly computations. Kim et al. [97,98] adopted a simple method for solving the VAV duct system optimization procedure: the Nelder–Mead downhill simplex method (DSM). It was simple in calculation and uncomplicated in logic. The optimization procedure was mainly composed of the calculation of hourly airflow rate, evaluation of the objective function, and the generation of a design solution. The airflow rate was calculated by an hourly building simulation program. Similar to the T-method, the objective function was the LCC including initial cost and fan operating energy. Mathematical models were developed. Then, the Nelder–Mead DSM was applied first to find the continuous duct size, and a penalty approach for integer/discrete programming was applied. This method used the hourly airflow rate rather than the design airflow rate for duct design. With respect to LCC, this method showed a 6–19% savings compared to the equal friction method, 2–13% saving over the static regain method, and 1–4% savings over the T-method.

Compared with duct size optimal design, there are also studies on computer-aided duct layout. Jorens et al. [89] pointed out that previous studies were mostly focused on optimization for duct size and material selection. They proposed an optimization problem that integrated both duct layout and size and material. It was characterized by discrete decision variables and nonlinear constraints. The optimization algorithm was developed in their later work. Bres et al. [99] developed a method for automatically generating HVAC distribution subsystems. It used minimum spanning tree algorithm to generate water distribution system. However, this method was designed for building performance simulation in early design stage. Issues such as collisions were not considered in this research. Brahme [100] developed generative design agents, which used heuristics and shortest-path algorithm for automatic generation of duct layout. For this algorithm, zone is defined as an architectural space conditioned by one air subsystem. Cluster is a set of air terminals within a certain range. Branch is a duct that connects two points. The design process is illustrated in Fig. 4. The building geometry and type of HVAC system is input for the design agent. Terminals and AHU are firstly placed in the design space considering air supply uniformity. Then terminals within 9–10 m are gathered to constitute a cluster, so the zone is divided into several clusters. For each cluster, a brunch across the short axis of the cluster is generated. Each terminal is then connected to the branch. At last, all cluster branches are connected to the start node (i.e. AHU) [100].

Table 2
Variables used for optimization [107].

Variable	Lower bound	Upper bound	Unit
Heating setpoint	20	2	°C
Cooling setpoint	23	27	°C
Rh setpoint	30	60	%RH
Starting delay	0	30	min
Stopping delay	0	60	min
Supply airflow rate	0.118	0.708	m^3/s
1st floor north window	4.76	14.3	m^2
1st floor south window	2.2	6.6	m^2
2nd floor north window	4.06	12.18	m^2
2nd floor southwest window	1.38	4.14	m^2
2nd floor southeast window	2.08	6.25	m^2
Thickness of concrete	0.05	0.25	m

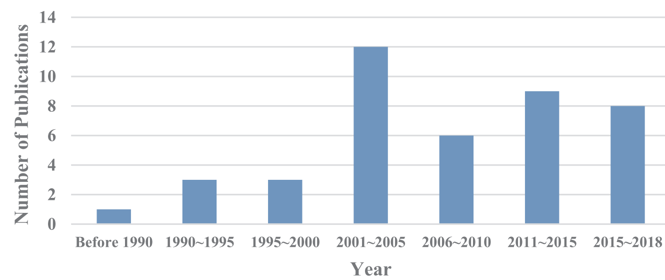

Fig. 5. Research trend of HVAC intelligent design.

5.7. System setting

System settings (i.e., air supply temperature, chilled water supply temperature, room air temperature, supply air static pressure, etc.) play an important role on system overall performance. For example, low chilled water temperature reduces pump energy consumption but may

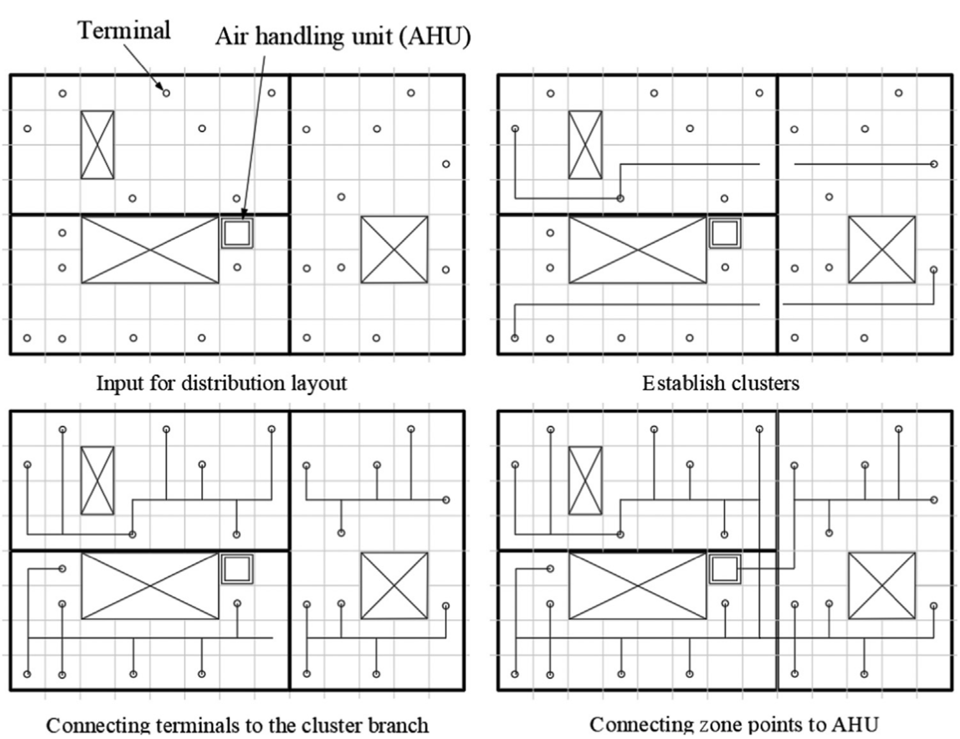

Fig. 4. Automatic ductwork layout procedure proposed by Brahme [100].

Table 3
Summary of optimization algorithms used to solve HVAC design problems.

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms
[63]	2014	Propose an optimal design method for the HVAC system of an apartment house	System type, plant capacity	Operation energy consumption	Multi-island GA
[64]	2011	Choose the best combination of HVAC system and building envelope	Azimuth, aspect ratio, insulation, wall construction, infiltration, window type, window wall ratio, mass, shading, heating/cooling setpoint, HVAC system type	LCC	GA, particle swarm algorithm, sequential search algorithm
[62,66]	2011	Select zoning strategy to maximize system efficiency	Grouping of zones served by the system, number of systems	Operation energy consumption	GA
[67]	2017	Generate zoning strategies for a given floor plan	Grouping of zones served by the system, number of systems	Initial cost, system efficiency, occupancy comfort	GA
[70]	2001	Simultaneous optimization of building fabric construction, HVAC system, and plant control strategy	HVAC on/off status, refrigerant mass flow rate, coil size, water circuits, fan size, building weight, glazing type, glazed area	Operation energy consumption	GA
[71]	2002	Identify optimum pay-off characteristic between energy cost and occupant thermal discomfort	HVAC on/off status, refrigerant mass flow rate, coil size, water circuits, fan size, building weight, glazing type, glazed area	Operation energy consumption, thermal comfort	Multiobjective GA
[76,79]	2005	Novel HVAC system configuration analysis	Component set, topological connections, operation strategy	Operation energy consumption	GA
[89]	2002	Duct and fan sizing	Pressure loss for each duct	LCC	DP
[90]	2002	Duct design standard considering duct sizes, variable time-of-day operating conditions and variable time-of-day utility rates	Diameter of each duct	LCC	GA
[91,92]	2003	Pipe and pump sizing	Diameter of each pipe and pumping equipment	LCC	GA
[93,94]	2002	VAV duct system sizing considering varying airflow rates	Duct size, fan size	LCC	DSM
[106]	2017	Find the optimal setting of indoor temperature and the battery state of charge of a PV system	PV capacity, room temperature setpoint	Operating energy consumption, thermal comfort	DP, GA
[107]	2010	Optimization of thermal comfort and energy consumption in a residential house	Heating setpoint, cooling setpoint, RH setpoint, starting/stopping delay, supply airflow rate, thickness of concrete, window size	Operating energy consumption, thermal comfort	NSGA-II
[108]	2011	Minimizing the energy consumption while maximizing the HVAC system efficiency	Supply air temperature and supply air static pressure	Operating energy consumption, thermal comfort	Strength Pareto evolutionary algorithm with local search
[109]	2012	Minimizing energy while maintaining indoor room temperature at an acceptable level	AHU static pressure setpoint and supply air temperature setpoint	Operating energy consumption, thermal comfort	Particle swarm optimization (PSO)
[110]	2014	Minimizing HVAC energy consumption and room temperature ramp rate	Supply air temperature and supply air static pressure	Operating energy consumption, thermal comfort	Evolutionary algorithm, PSO, harmony search algorithm

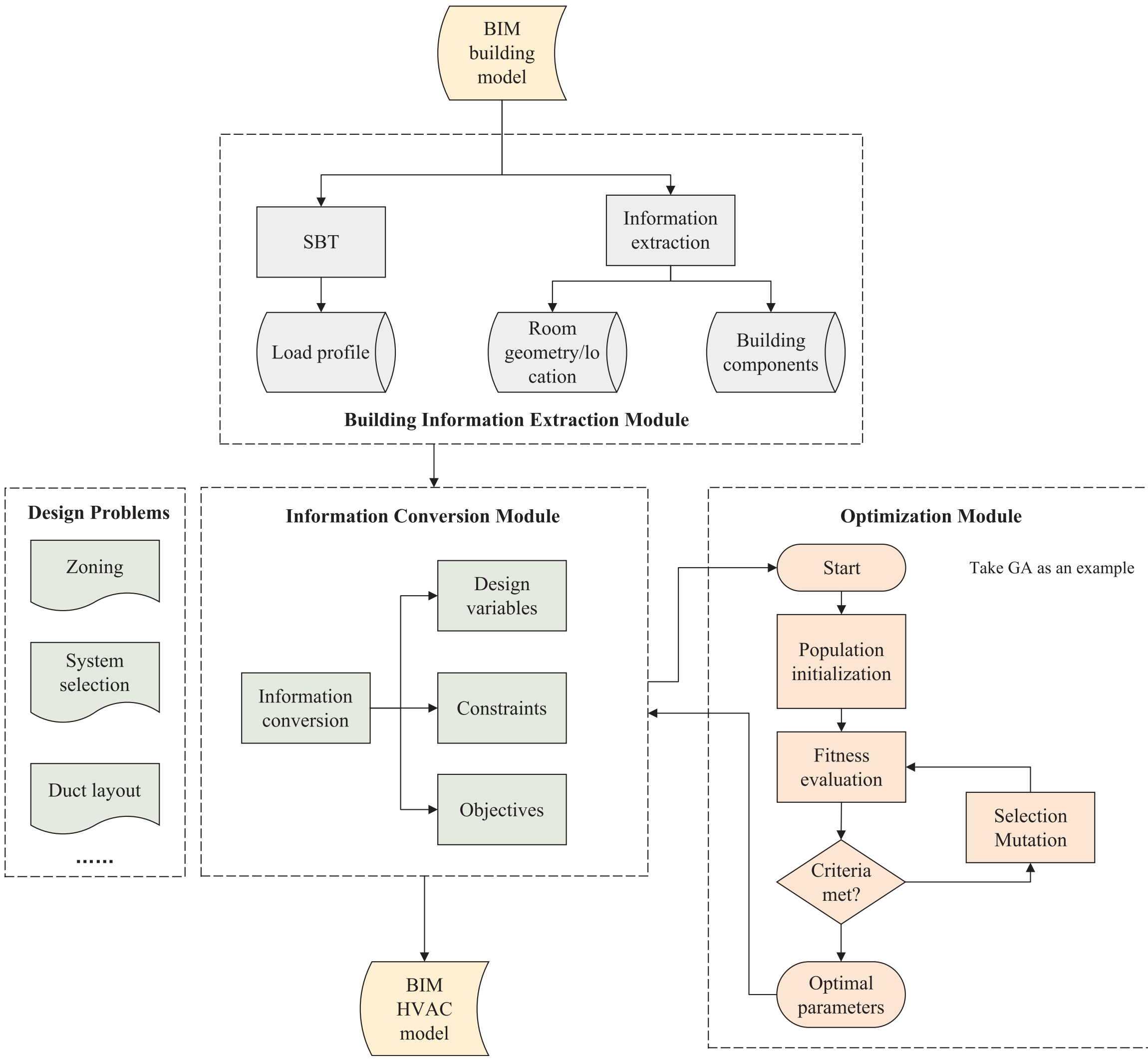

Fig. 6. Framework of integrated HVAC design and optimization process based on BIM.

increase chiller energy consumption. Chilled water temperature setting is an optimization problem with multiple variables, which should be carefully considered from a global perspective. However, for industrial design practice, the system setpoints are usually determined in accordance with the design condition based on designers experience and rule of thumbs. It is usual that the setting of a chilled water system deviates from the design condition for many years, resulting in energy wastage. An approach to solve this problem is called model-based design (MBD), which relies on CI to optimize the HVAC system. The typical optimization model of MBD consists of three parts:

- models representing the HVAC system or its components,
- optimization objective and constraints,
- optimization algorithm, which is used to find the best solution.

One or several mathematical models are developed to represent the system or components. The models are used to evaluate the system performance during the optimization process. Two types of models (i.e., physical and data-driven) are mostly studies for MBD. Physical models offer a detailed mathematical description of the HVAC system, which is more accurate and reliable. Software, such as EnergyPlus and TRNSYS, is often integrated to simulate the HVAC process. However, a detailed simulation is time-consuming especially for complex systems. The data-driven model is an alternative approach for modeling HVAC systems. The effectiveness of such models for system setting has been demonstrated in other research fields such as wastewater treatment system design [101–103] and renewable energy producing using building wastes, wind and solar [104,105]. The most common optimization objectives are operating energy and thermal comfort. The input solutions are the values of HVAC system setpoints. Normally, users set up constraints, which keeps the solution within a physically reasonable region.

Pombeiro et al. [106] developed three optimization models: (1) dynamic programming with simplified thermal models (STM), (2) GA with STM, and (3) GA with EnergyPlus. They are used to find the optimal setting of indoor temperature and the battery state of charge of a photovoltaic (PV) system in order to minimize energy cost and maintain thermal comfort. Magnier et al. [107] considered a number of design variables in the optimization, as presented in Table 2, including both HVAC system setpoints and building geometric parameters. They used ANN to model the building and the system. The multiobjective GA as used to find the optimal setpoints. Kusiak et al. [108–112] performed a series of studies to optimize system performance through adjusting setpoints. They focused the setpoints on supply air temperature and supply air static pressure. The objective system performance indices included total energy, room air temperature ramp, and indoor air quality. A specific multilayer perceptron neural network was developed in each research to represent the system. Data used to train the network were collected from an experiment conducted in a real commercial building. Different optimization algorithms (i.e., evolutionary optimization algorithm, particle swarm algorithm, harmony search algorithm, and firefly algorithm) were tried and compared with each other to find the optimal solution (i.e., supply air temperature and supply air static pressure). The results showed that considerable energy could be saved with optimized setpoints while maintaining indoor thermal comfort and air quality.

6. Discussion

6.1. Research trend of CI application in HVAC design

When Alfred Wolff designed the first air-conditioning system in 1902 for the New York Stock Exchange, it took a year to complete the drawings [114]. Computers have greatly improved the design efficiency, especially in recent years when intelligent technologies emerged. HVAC intelligent design is becoming an important research area because HVAC design quality greatly impacts the whole building operation and energy efficiency. Fig. 5 shows the number of publications reviewed in this paper since 1989. The number of publications slightly dwindled down during the period from 2006 to 2010. However, on the bright side, there is an increasing number of researchers devoted to the study of HVAC intelligent design.

6.2. Typical workflow of HVAC optimization design

HVAC design is a complicated process containing several procedures. The design cannot be simplified into a single mathematical problem and be solved by a single method or algorithm. Most of the studies discussed in this paper focus on a specific design problem such as how to select proper system types or equipment. Though the design problem varies with each other, many design problems are transformed into optimization problems; thus, the problems can be solved automatically by computer algorithms. Optimization deals with finding an optimal solution to minimize or maximize an objective function with several variables, which are subject to their constraints. This approach is widely used in operations research, management science, and engineering design. Three key elements, i.e., design variables, constraints, and objective, comprise an optimization problem. The design variables are the parameters that control the optimization structure. They can be either continuous or discrete variables. The objective function $F(x)$ being optimized measures the effectiveness of the design. This function could be formulated by a single function or multiple objectives as follows:

$$F(x) = \{f_1(x), f_2(x), \ldots, f_p(x)\}$$

For the HVAC design problems discussed in this paper, the optimization objectives are mostly one or several of the following aspects:

- initial cost,
- operation energy consumption,
- maintenance cost,
- thermal comfort,
- indoor air quality.

The limits of the design variables are known as constraints. They set the searching boundary ensuring that the optimal solution obtained follows physical laws. Table 3 presents a summary of optimization problem formulations discussed in this paper. GA and its modified versions are most widely used methods to solve optimization problems, owing to their robustness and easy implementation. One of the main challenges for a robust optimization algorithm is to define an efficient evaluation method for the fitness of a solution. For example, when using operating energy consumption as the objective, the direct method is to build an energy model and use the energy output for iteration. However, iterations are very time-consuming as thousands of them are required. Two methods are used to solve this problem. The first one is the use of a simplified model as an alternative for trading accuracy for efficiency. The second one is to train a data-driven model beforehand using simulated data. Data-driven models run much faster than the whole building simulation model. ANN is the most popular method for training owing to its superior nonlinear characteristics. However, different data-driven models have to be trained for different objectives. For example, when evaluating a multiobjective considering both operating energy and indoor air quality, separate models have to be trained as they are influenced by different factors. Extensionality is another consideration for data-driven models. If the test point is out of the training range, the data-driven model will be unreliable. Therefore, it is required that all possible situations should be covered when determining the training dataset.

6.3. Integrated HVAC design and optimization process

The CI technologies reviewed in this paper are aimed at facilitating the design process. Many methods and tools are developed and built. However, most of these tools and methods are not used and finally neglected. One major reason why they are very difficult to incorporate into conventional design practice is that the problem formulation and defining a design problem in mathematical approach require high skills and experience. Such skills and experience are beyond the capability of HVAC engineers. Moreover, the conventional design is conducted in 2D graphs. Design information has to be extracted manually. The extraction itself is time-consuming and tedious. These are the reasons that all activities are limited to specific research areas and it is seldom that any of the AI methods are used in HVAC design practice.

In recent years, building information model (BIM) is gaining increasing popularity in building design. BIM is a digital representation of building characteristics and functionalities containing files in standard format, which can be extracted, exchanged, or networked to support decision making regarding a building or other built assets [113]. All building information is structurally stored in the BIM model complying with some type of standard format. Therefore, it is easy to extract required information using computer programs automatically. Moreover, design changes can be made with minor intervention. For example, if you want to change the duct diameter from 400 mm to 500 mm, all you need to do is change the diameter number. The corresponding diagram and drawing will be generated automatically. BIM makes the exchange between design and optimization possible. In the light of BIM and the typical solution procedure for optimization problems discussed in the previous section, an integrated design and optimization framework is proposed as shown in Fig. 6.

There are three core modules in this framework. They are *information extraction module*, *information conversion module,* and *optimization module. Information extraction module* is designed to read a BIM file and extract information from it. A tool called SBT is embedded in this module [115]. It is developed by Lawrence Berkeley National Laboratory. It is able to convert a BIM model to an EnergyPlus file and produce a load profile for further analysis. Once the BIM building model is available, the required information for each HVAC design procedure can be extracted automatically using this module. For example, information such as room geometry, location, function, and load profile will be collected to conduct zoning analysis. When the design information is ready, the information is passed to the *information conversion module*. This module is a medium between the engineering design problem and optimization problem, which is in mathematical form. In this module, the components, i.e., design variable, objectives, and constraints, will be formulated and prepared for optimization analysis. For the *optimization module*, it is designed to conduct the optimization calculation. Several optimization algorithms such as GA and DP are available within this module. Users can choose the preferred one or follow the recommended advice given by this tool. In Fig. 6, GA is illustrated as an example. Finally, the calculated optimal solution is again converted into the engineering format using the *information conversion module*. This tool can be designed as a plug-in of the BIM software, which can help engineers make better decisions and without bothering on coping with complicated mathematical problems.

7. Conclusions and further work

This paper has reviewed the problems, solving methods and application examples of HVAC system optimization design. The main findings and contributions of this paper are summarized as follows.

(1) The HVAC design process contains seven procedures. According the problem characteristic and solving approaches, this paper defines three type of optimization design problems, i.e. model estimation, decision making and uncertainty analysis. Corresponding solving methods and application methods are also presented. Other researchers can refer to this result.
(2) For all three optimization design problems, decision making is most essential. This paper introduces three solving methods. GA is the most widely used one. Apart from basic version of GA, several modified versions have been developed to strengthen performance. Design variables, constraints, and objective are three key elements to constitute a GA-based optimization problem. Constraints defines the selecting range of design variables. The constraint setting values should be in accordance with physical laws as well as mandatory design codes. Objective formulation directly influences problem solving efficiency.
(3) Building load calculation and objective formulation for GA-based optimization belong to the category of model estimation problem. Physical-based method and data-driven method are both applicable to solve a model estimation problem. Choosing which method depends on many factors, which include system design phase, estimation accuracy, time limit, available building and system information etc. Physical-based method is more accurate and the developed model can be used to conduct further parametric analysis, but establishing a detailed physical model is time-consuming and requires much detailed information. Besides, complex physical model calculation often has heavy computing burden. Whereas data-driven method is less accurate, but is much faster and requires less information. So data-driven method is more suitable for initial design phase to get a general profile of system energy demand and objective formulation of a complicated GA-based optimization problem. However, it should be noticed that the data-driven model is less extensible, so training cases of a data-driven model have to be as diverse as possible to cover design condition of the target building or system, or the predicted result is unreliable.
(4) As discussed in Section 6.2, HVAC optimization design process follows a typical workflow. This paper proposes a framework of an integrated automated optimization design tool. The framework is developed based on BIM and the extracted typical optimization design workflow. It aims to connect various design stages by implementing structured information transfer between them and ultimately improve design efficiency and quality. However, this framework is just a conceptual version, more research is needed. We will continue working on this topic to put this idea into practice.

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Declarations of interest

None.

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