Automatic Design Synthesis and Optimization of Component-Based Systems by Evolutionary Algorithms

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Abstract. A novel approach for automatic design synthesis and optimization using evolutionary algorithms (EA) is introduced in the paper. The approach applies to component-based systems in general and is demonstrated with a heating, ventilating and air-conditioning (HVAC) systems problem. The whole process of the system design, including the initial stages that usually entail significant human involvement, is treated as a constraint satisfaction problem. The formulation of the optimization process realizes the complex nature of the design problem using different types of variables (real and integer) that represent both the physical and the topological properties of the system; the objective is to design a feasible and efficient system. New evolutionary operators tailored to the component-based, spatially distributed system design problem have been developed. The process of design has been fully automated. Interactive supervision of the optimization process by a human-designer is possible using a specialized GUI. An example of automatic design of HVAC system for two-zone buildings is presented.

1 Introduction

There are generally two phases in a design process:

- Conceptual design
- Detailed design

During the conceptual design phase, strategic design decisions are usually taken by the human designer based on experience and knowledge. These choices lead to one or more possible schematic representation(s) of the system. Repeated consideration of similar problems quite often results in a set of "typical" design solutions for predefined cases.

The conceptual design is a creative process and is highly subjective. The detailed design process identifies possible candidate solutions that meet the requirements and provide the necessary level of performance [12]; in contrast, this stage involves numerical analyses and simulation and occasionally optimization.

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The development of component-based simulation techniques [3,5] made possible the investigation of changes in system operating variables and parameters. Studies considering a fixed system configuration are now relatively easy to compile [7]. Existing design options allow the designer to chose a particular configuration from a list of prescribed systems [4] or to develop a user-defined system [2,6]. The former approach presents a limited range of possible solutions and the latter is realized only by time-consuming and error-prone procedures.

An alternative approach is proposed in the paper offering a new degree of freedom in the design process. Using the technique, strategic design decisions concerning the system type and configuration are investigated as part of the design optimization process, instead of being predefined. This approach allows alternative, **novel** system configurations to be explored automatically and hence, the “best” design in terms of both the feasible configuration and optimal set of sizing parameters to be determined.

It is well known that for a given design problem, a number of plausible system configurations exist [10]. The proposed approach combines the automatic generation of alternative system configurations with the optimization. Variables and parameters describing the system configuration, the component set and the topological links, form part of the optimization search-space [13]. EAs have been selected to solve this multi-modal problem because they are particularly appropriate for tackling complex optimization problems [1].

New evolutionary operators, tailored to the specific problem of secondary HVAC system design, have been developed. The component set and the topological interconnections have been encoded into the chromosome of the EA. This has been combined with the physical variables describing the thermal and air mass transfer through the HVAC system into a “genome” (a data structure, which combines several types of chromosomes). The objective is to design a feasible and energy efficient system. The system input is a “design brief”, a standardized description of the design requirements and constraints. The output from the system is a ranked list of suggested design solutions ordered by their cost. The cost is based on component size and energy consumption. The process of design is fully automated. A computational module has been produced in Java, given a performance specification and a library of system components, can synthesize functionally viable systems configurations. In addition, the specialized GUI allows interactive supervision of the design process by a human-designer. An example of automatic design of HVAC systems for two-zone buildings is given as an illustration of the technique.

2 Automatic Design Synthesis and Optimization by EA

2.1 Concept of the Approach

The concept of the proposed approach is that the design synthesis can be represented as a constraint-satisfying optimization problem. In this way, the design synthesis, including system configuration generation and parameter optimization as well as the overall system performance optimization is integrated into one search problem. This problem formulation combines the search for a feasible system configuration (comprising the list of particular components used and their interconnections) with the minimization of the energy (and possibly capital) costs. A feasible configuration is one that fulfills both the design and engineering requirements.

The computational mechanism used to solve the problem is based on EA [1,8]. This technique has proven to be powerful and robust in solving mixed variable, nonlinear and discontinuous problems. The EA searches from a population of points, each representing a particular candidate solution. It needs only the value of the objective function and operates using a coding of the parameter set not the parameter values. The evaluation of a given system includes checks that the configuration satisfies the connectivity constraints and the other specific requirements of the system; in this case, that the supply air conditions satisfy the zone loads. Graph algorithms have been used to verify these requirements [14].

The approach is concerned with identifying system configurations using a library of typical components performing elementary transformations. A typical list of components of a secondary HVAC system is given in Table 1.

Table 1. List of components (example for a secondary HVAC system)

ID	Type	Description
0	Div	Divergence tee
1	Mix	Mixing tee
2	Heat	Heating coil
3	Cool	Cooling coil
4	Steam	Steam injection
5	Zone	Zone
6	Ambient	Ambient environment

The approach is generic and could be applied to other similar design synthesis and optimization problems. These include building architectural design, electronic hardware design, pipeline and sewage network design. The approach maximizes the potential for generating novel system designs, but needs to determine whether or not the system configurations conform to the connectivity constraints. It forms a highly constrained mixed integer-real multi-modal optimization problem.

Characteristics of the specific search problem are:

- the solution space is multi-modal, with the viable system configurations being distributed in a discontinuous manner throughout the search space;
- the number of performance optimization variables changes with the system configuration, and therefore, location of the solution in the search space.

2.2 Evolutionary Synthesis and Optimization of the System Configuration

An initial population is created randomly in which each member is a chromosome consisting of a coding of the components used together with their links. This population is then evolved through successive epochs using mating and mutation to improve the "fitness" of the population. Each chromosome is formed from the system connectivity [14], component capacity and air mass flow rate variables. It is possible for configurations in a given population to have different numbers of components, hence the number of capacity and flow rate variables could be different. The structure of genome, depicted in Fig.1 has been developed to handle this complexity. Essentially, a more flexible data structure is designed to combine chromosomes with variable length in an object-oriented manner. The benefit of the use of the data structure is the use of directed crossover in optimizing the duties. Unlike the loose chromosome set implementation seen in some other implementations, this structure allows relationship and interaction to be defined among its member chromosomes. It allows the consistency of the genome to be maintained although there are operators performing on chromosome level. This implementation is more generic in that:

- It does not require equal/fixed length member chromosomes;
- It can take any type of member chromosomes

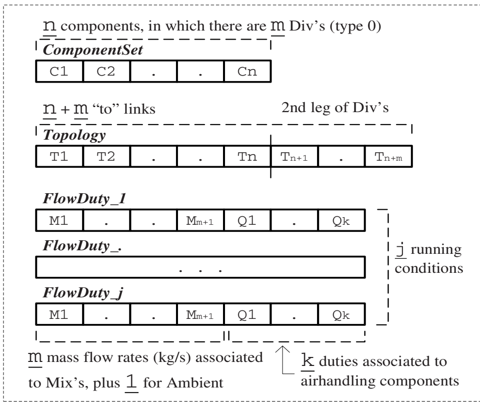

Fig. 1. Genome structure

Each problem variable is viewed as a *gene*. It can be integer (for the component ID number, its position and links (topology) or real (for the coil duty or mass flow rate). A collection of *genes* forms a *chromosome*. Examples of such chromosomes having a clear interpretation in the HVAC system design are [14]:

- *ComponentSet* (list of components present in a particular configuration);
- *Topology* (Modified adjacency list encoding of the network, where "To" links between the components are listed);
- *FlowDuty* (Real-encoded air mass flow rates and component duties for each running condition).

In short, the *genome* is a collection of chromosomes that fully describe structure and operation of a specific system. A sample of genome is presented in section 4.

2.3 Fitness and Constraints Formulation

The design synthesis and optimization problem has been formulated as a constraint satisfaction problem, which in general can be described by:

Minimize: $f(X,Y), \quad X=(x_1,\ldots,x_{n1})\in\Re^{n1}$

$Y=(y_1,\ldots,y_{n2})\in N^{n2}$

Such that:

$$
\begin{aligned}
& l_i \le x_i \le u_i, \quad \forall i \in (1,\ldots,n1) \\
& g_j(X) \le 0.0, \forall j \in (1,\ldots,q) \\
& h_j(X) = 0, \quad \forall j \in (q+1,\ldots,m1) \\
& l_i \le y_i \le u_i, \quad \forall i \in (1,\ldots,n2) \\
& h_j(Y) = 0, \quad \forall j \in (q2+1,\ldots,m2)
\end{aligned}
$$

And:

$$
\begin{aligned}
& l_i, u_i \in \Re^n \\
& l_i \le u_i, \forall i \in (1,\ldots,n)
\end{aligned}
$$

The EA attempts to find a system configuration that minimizes the system energy consumption subject to both the system configuration and system operation being feasible. The feasibility of the system configuration can be defined by a set of equality constraints, $h_j(Y)$, whereas the feasibility of the system operation is described by a set of inequality constraints, $g_j(X)$. In fact the system operation includes two equality constraints on the zone conditions, but these have been converted to inequality constraints by applying a tolerance, , to the equality: $|h_j(X)| - \delta \le 0.0$. Since it is not possible to evaluate the energy use of an infeasible topology, fitness of solutions violating the topology constraints is evaluated by the degree of violations.

The fitness, $F(X,Y)$, is derived from a linear exterior penalty function and is formulated for function minimization:

$$
F(X,Y)=\begin{cases}
w_f f(X,Y), & \text{If feasible;} \\
w_f f(X,Y)+\sum_{j=0}^{q} w_j g_{o,j}(X)+\sum_{j=q+1}^{m} w_j \left(|h_{o,j}|-\delta\right), & \text{else if topology feasible, operation infeasible} \\
\sum_{j=q+1}^{m} w_j |h_{t,j}| & \text{else (topology infeasible).}
\end{cases}
$$

Where: subscript *o*, refers to the operation constraints and subscript *t*, to the topology constraints; all $g_{o,j}$ and $\left(|h_{o,j}|-\delta\right)$, have values ≥ 0.0 (are infeasible); and w_f and w_j are the objective and constraint function weights.

Several sets of fundamental and user-defined and controlled constraints are imposed on configurations generations. Generally, they consist of [14]:

- component-related rules
- connection-related rules
- process-related rules

It should be mentioned that the approach applied to the problem is **open** and allows easily to add/modify any group of constraints/rules.

3 Problem-Specific Operators

The optimization has two connected problems; search for feasible configurations and optimization of operations of the feasible configurations found. The latter can only be performed when the configuration is feasible. The effective solution of the search for feasible configurations is therefore of paramount importance. A set of problem-specific operators for mutation and recombination of topologies have been studied, to improve the chance for a candidate configuration to be feasible.

3.1 New Operators Definitions

Two operators have been defined for mutation of topology chromosomes. The "Component link mutation" (LINK) is based on the generic swap-type mutation that inverses the position of two randomly selected genes. For a topology chromosome, inversion of the integers representing the "To" links effectively exchanges two branches in the network, as illustrated in Fig.2. The number of swaps to be performed can be specified as a parameter of the operator. The advantage of the operator is its exploration power, but the probability of damaging the connectivity requirement of a topology is high. As a mutation operator, LINK increases the exploration capabilities of the algorithm by swapping the links, not only the components themselves.

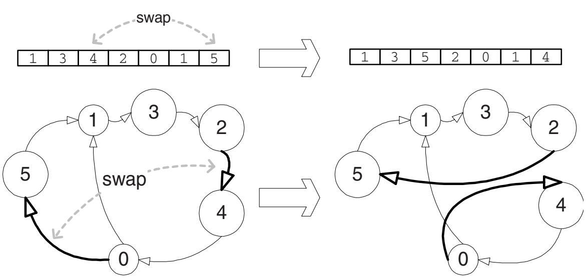

Fig. 2. Example of Component links mutation operator

The second topology operator is "component position mutation" (POS), illustrated in Fig. 3. The position of component <2> and component <0> in the network are exchanged by sequentially swapping the "To" and "From" links belonging to each component. If either component had had more than one "To" or "From" link, graph based analysis would have been applied to determine which link can be swapped to ensure preservation of the network connectivity. The advantage of this operator is that if a topology has already satisfied, the connectivity requirement, further operations do not generate topologies that violate it. The POS operator generates fewer infeasible solutions than the LINK operator, but it is weaker at exploring new topologies.

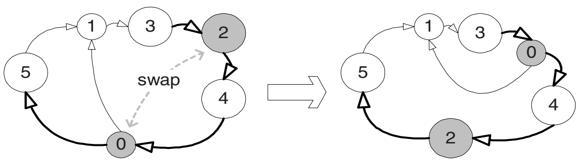

Fig. 3. Example of swapping mutation operator

The configuration of an HVAC system can be considered as a network of components in which air is flowing. Accordingly, optimization methods developed for the so-called Travelling Salesman Problem (TSP) are intuitively relevant. Goldberg [8] introduced "partially matched crossover" (PMX), which has shown its usefulness in solving the TSP. The PMX was adapted as a topology recombination operator with a minor modification to allow multiple connections to a single node. When a child chromosome is produced, the PMX for topology tries to preserve chunk of chromosome from one parent, completing the chromosome with parts of the other. In order to maintain the correct form of adjacency representation for a network, genes from the second parent often have to be repaired. This limits the inheritance of features from the second parent. In addition, any repair of the genes is executed without consideration of the preservation of connectivity. This results in a high probability that a pair of parents who themselves are already connected, will produce unconnected children. This characteristic has a significant impact on the performance of PMX in searching topologies, demonstrated by the results in the next section.

A new topology recombination operator, "adjacent component crossover" (ADJ), has been implemented in order to enhance both connectivity and propagation of features. The procedure is based on the assumption that the adjacency of specific components is useful feature for an HVAC configuration. The ADJ operator performs minimal relocation of components in the clone of one parent, so as to make the pair of adjacent components in the other parent, adjacent in the child also. The procedure is illustrated in Fig. 4. Firstly, the parent chromosomes are cloned and following steps performed:

1) A component that is present in both topologies is selected at random as the base component (component <1> in this instance).
2) The component next to the base component is identified in both topologies respectively. If this component is same in both topologies, or if it is absent from either topology, restart from step 1. The feature of parent A identified in this

example, is the adjacency of <1>→<3>, whereas the feature of parent B is the adjacency of <1>→<2>.

3) The algorithm that exchanges components in the POS operator is used to swap components in parent A in the example. This ensures the preservation of connectivity in the child A'. So for parent A, these operations are; where <3> is linked from <1>, swap <3> with <2> so that <1> and <2> become adjacent.
4) Step 3 is then repeated for parent B to achieve the adjacency feature (<1>→<3>) in parent A.

The result of these operations is that the child preserves most of the network structure of the parent, while acquiring a new feature from a second parent.

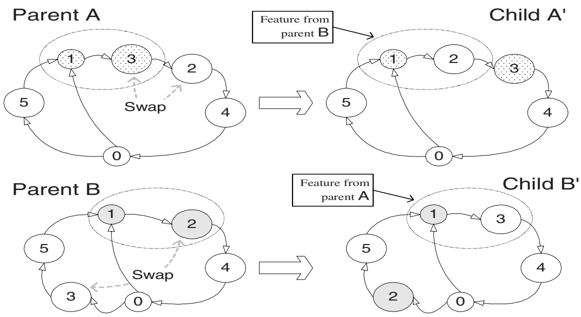

Fig. 4. Example of exchange-adjacent component crossover

3.2 Evaluation of New Operators

Two test procedures have been performed to evaluate the effectiveness of the new operators. In the first test procedure, the operators are used to generate new individuals from a pre-prepared population. The proportion of feasible topologies generated in the children of the initial population is compared to the number of new individuals. This measure gives the probability that the operator will produce feasible topologies from an existing topology.

Two initial populations are prepared, both based on a set of 15 components. The first population is filled with randomly initialized topologies and the second with feasible topologies. The feasible topologies are generated at random and tested for feasibility *a priori*. The operator under test continually selects individuals from the initial population, producing new individuals, until 10,000 new chromosomes have been produced. The same test is repeated on a given operator 20 times. The mean and standard deviation of the results are given in Table 2.

Table 2. Number of feasible solutions out of 10,000 individuals produced by mutation and crossover operators from random population and all-feasible population

Mutation	From Random Mean (stdev)	From Feasible Mean (stdev)	Crossover	From Random Mean (stdev)	From Feasible Mean (stdev)
FLIP (p = 0.1)	2.6 (1.43)	253.3 (18.1)	1P (p = 1.0)	0.9 (1.04)	118.7 (19.0)
RAND (p = 1.0)	99.1(12.0)	100.0(11.1)	PMX (p = 1.0)	95.9 (8.6)	641.0 (19.4)
LINK (swap = 1)	102.9 (20.0)	2439.7 (30.3)	ADJ (p = 1.0)	132.6 (24.1)	6221.2 (51.3)
POS (swap = 1)	141.3 (28.6)	6326.6 (35.7)			

The proposed topology operators are compared with "flip gene mutation" (FLIP), "randomization operation" (RAND) and "1-point crossover" (1P). Table 2 demonstrates that the number of feasible solutions generated by the topology-specific operators are significantly higher than those generated by the more conventional operators. Both POS mutation and ADJ crossover have more than 60% probability of producing new feasible topologies from feasible parents. Conventional operators for integer chromosomes (FLIP mutation and 1P crossover) have only 1%~3% chance of producing feasible individuals from feasible parents.

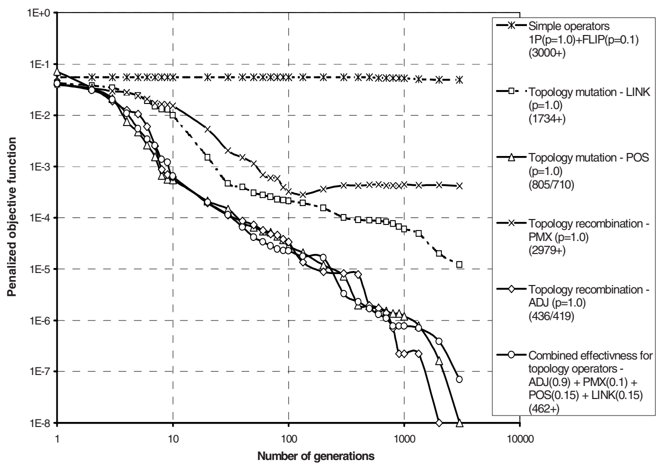

Fig. 5. Effectiveness of evolutionary operators in searching a specified topology

The second evaluation procedure tests convergence. In the procedure, a conventional configuration for a HVAC system was selected, depicted in Fig. 6. The operation of the selected configuration, including the component capacities and airflow rates, were optimized. The capacities and flow rates were then fixed and the system configuration subjected to further optimization, using the different operators. The optimal configuration in this case must be the original configuration and hence convergence on this solution can be used as a measure of operator performance. Figure 5 illustrates the rate of convergence for various operators.

The numbers given in the notation are the mean generations required to find the optimum configuration from 30 runs. The '+' sign indicates that the topology was not found in every trial run, otherwise standard deviation is given. Fig. 5 demonstrates the poor convergence using the conventional operators compared to the new problem-specific operators.

4 Automatic HVAC System Design Synthesis and Optimization

To demonstrate the design synthesis approach, consider the HVAC problem: Design the optimal HVAC system for a small office building in Oklahoma, USA. Three typical design conditions are selected to represent the operation in summer, winter, and swing season. Fig. 6 shows a conventional system with its optimal operation parameters in the summer condition. One of the auto-generated configurations is presented in Fig. 7 (encoded), and in Fig. 8 graphically.

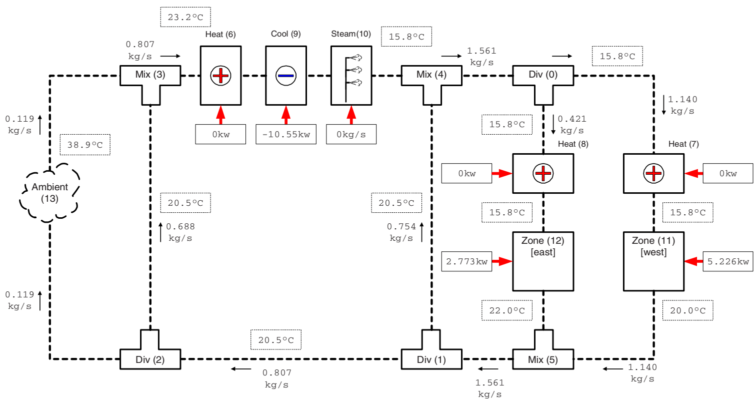

Fig. 6. A conventional HVAC system configuration (summer condition)

	Div				Mix				Heat		Cool		Steam	Zone		Ambient
CompSet	0	0	0	0	1	1	1	1	2	2	3	3	4	5	5	6

Topology	5	7	1	6	13	7	0	4	9	5	14	4	11	2	6	3	10	12	15	8

	Flow rates (kg/s)					Heating (kW)		Cooling (kW)		Steam (kg/s)
FlowDuty_1	0.064	0.592	0.029	0.388	0.072	0	0	-3.30	-5.88	0
FlowDuty_2	0.064	0.285	0.025	0.172	0.117	0.12	0.90	0	0	0
FlowDuty_3	0.096	0.0	0.001	0.948	0	0	0	0	0	0

Fig. 7. The genome for the generated configuration

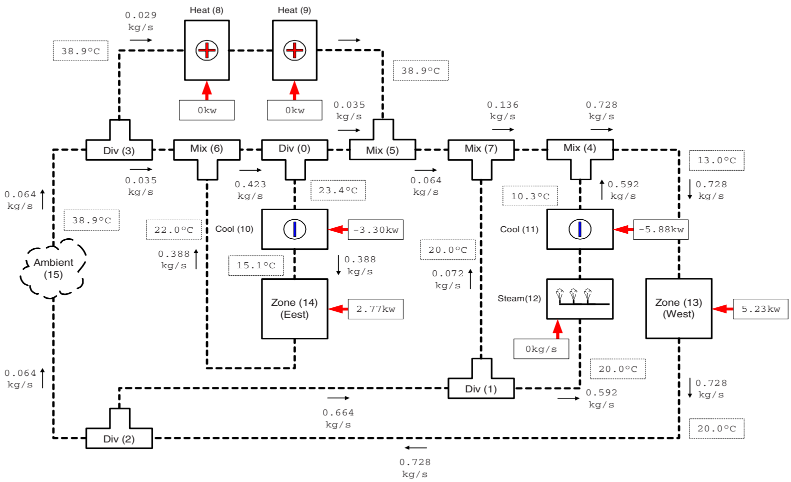

Fig. 8. Configuration generated automatically by the new approach (summer condition)

The minimum energy consumption associated with the conventional and generated configurations is compared in Table 3. The results illustrate both the ability of the automated design synthesis approach to find a viable HVAC system design and that the system is more energy efficient saving ~800kWh or 9% of the energy consumed by the optimized conventional design solution.

Table 3. Energy consumption for conventional and automatically generated configurations

Season	Conventional Configuration			Generated configuration			Total energy saving (kWh)
	Total Heat/Cooling Consumption (kWh)	Total circulation consumption (kWh)	Total energy consumption (kWh)	Total Heat/Cooling Consumption (kWh)	Total circulation consumption (kWh)	Total energy consumption (kWh)	
Summer	6857.5	396.5	7254.0	5960.5	136.5	6097.0	1157.0
Winter	858.0	71.5	929.5	611.0	65.0	676.0	253.5
Spring/Autumn	0.0	377.0	377.0	0.0	988.0	988.0	-611.0
Annual Total			8560.5			7761.0	799.5

4 Conclusions

A new approach for automatic design synthesis and optimization using EAs is introduced in the paper. The approach applies to component-based systems in general

although the focus of this paper has been on secondary HVAC system problems. The whole design process is treated as a constraint satisfaction problem. The problem formulation is complex, using different variables to represent the physical and topological properties of the system. The problem objective is to design a feasible and efficient system. EAs have been shown to solve numerically complex search problems such as this. Several problem-specific operators, tailored to the component-based spatially distributed systems design, have been developed and evaluated. The results of evaluation of these operators illustrate their superiority in comparison with conventional operators for the mutation and crossover of integer genes.
The process of design can be fully automated, commencing with a design brief and resulting in a rank ordered set of optimal configurations. An example of the automated design of a secondary HVAC system for two-zone office building was presented. The synthesized system design showed energy savings of about 800 kWh (or 9%) compared to the optimal, conventional system, based on the performance over three season-typical days. This result demonstrates the potential of the approach to automatically generate viable novel HVAC system configurations that can yield improved energy performance compared to conventional design solutions.

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