Optimization Methodologies for Building Performance Modelling and Optimization

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Abstract

Buildings account for approximately 40% of the global energy consumption and 36% of total carbon dioxide emissions. At present, high emphasis is given on the reduction of energy consumption and carbon footprint by optimizing the performance and resource utilization of buildings to achieve sustainable development. Building performance is analyzed in terms of energy performance, indoor environment for human comfort & health, environmental degradation and economic aspects. As for the energy performance analysis, this can be best modeled and optimized by a whole building energy simulation tool coupled with an appropriate optimization algorithm. Building performance optimization problems are inherently multivariate and multi-criteria. Optimization methodologies with different characteristics that are broadly classified as Adaptive, Non-adaptive and Pareto Algorithms can be applied in this regard. The paper discusses the applicability of the aforementioned optimization methodologies in building performance optimization for achieving realistic results.

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1. Introduction

Buildings are responsible for nearly 40% of the global energy consumption and approximately 36% of the total carbon dioxide emissions [1]. In order to achieve sustainable development, at present, high emphasis is given for the reduction of energy consumption and carbon footprint by optimizing the performance and resource utilization of buildings. Building performance can be analyzed based on the following criteria:

- Energy performance
- Indoor environment for human comfort and health
- Environmental degradation
- Economic aspects

Building energy modeling is one of the strategies that can be applied for building performance analysis. Energy modeling is one of the key areas of the broader discipline of building simulation, a domain that analyzes thermal aspects, day-lighting, moisture, acoustics, airflow and indoor air quality [1]. A whole building energy simulation tool such as *EnergyPlus* can be used for this purpose. However building energy simulations are generally used on a scenario-by-scenario basis, with the designer generating a solution and subsequently having the computer evaluating it. This is however, a slow and a tedious process and generally, only a few cases are evaluated from a large range of possible scenarios. By coupling an appropriate optimization technique with the aforementioned whole building energy simulation tool, it is possible to optimize the energy performance of buildings by determining the best combination of building design variables, subject to predefined constraints [2]. Although a wide range of optimization techniques are in existence, not all of them are applicable to building performance optimization.

The paper initially provides an overview of the existing optimization methodologies and subsequently discusses their applicability in optimizing building performance for achieving realistic results.

2. Optimization Methodologies

In optimization, the best solution that satisfies preset objectives, among a field of feasible solutions, is sought under the restriction of certain constraints. Optimization utilizes mathematical techniques systematically to model and analyze certain quantitative measures to get the best course of action possible for a decision problem [3]. An optimization problem consists of:

- A set of independent variables or design parameters
- A set of constraints that bound the respective domains of the independent and dependent variables
- An objective function to be optimized

Optimization methodologies with different characteristics can be broadly classified as adaptive, non-adaptive and Pareto algorithms.

Non-adaptive algorithms initially determine all search points at which the objective function is to be evaluated. Subsequently they evaluate the objective function at all aforementioned locations and determine the optimal solution approximately. Design of experiments and random sampling come under this category.

Direct search methods, gradient-based strategies and evolutionary search methods are categorized as adaptive algorithms. They take the results of the previous evaluations into consideration in determining a new search point. Direct search algorithms handle the objective function only through ranking a countable set of function values. It does not involve the partial derivatives of the objective function and hence it is also called non-gradient or zeroth order method. Algorithms of cyclic coordinates, Hooke and Jeeves method [4], Rosenbrock method [5], simplex method of Nelder and Mead [6], Powell's conjugate directions method [7] are some of the main direct search optimization techniques.

In the Hooke and Jeeves method [4], an initial step size is chosen and the search is initiated from a given starting point. The method involves steps of exploration and pattern search as shown in Figure 1. Exploration is used to explore the local behaviour of the objective function and the pattern search is used to take advantage of the pattern direction. In this method, the pattern direction is established with a search in the coordinate directions. Once a pattern direction is established, new information related to the function is available. Hence a new set of orthogonal directions can be developed using this information.

In Rosenbrock's method [5], the search is carried out in *n* orthogonal directions at any stage. New orthogonal directions are established at the subsequent stages. The orthogonal setting makes this method robust and efficient.

The simplex method of Nelder and Mead [6] makes use of the geometric properties of the *n*-dimensional space. In an *n*-dimensional space, *n*+1 points form a simplex. An initial simplex in *n*-dimensions is easily created by choosing the origin as one corner and *n* points, each marked at a set distance, c from the origin along the coordinate axes as shown in Figure 2.

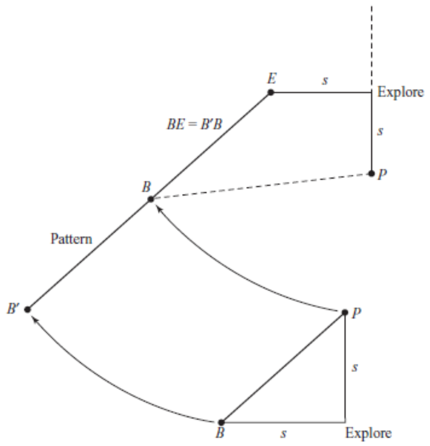

Figure 1: Exploration and pattern search in the Hooke and Jeeves algorithm

Source: [8]

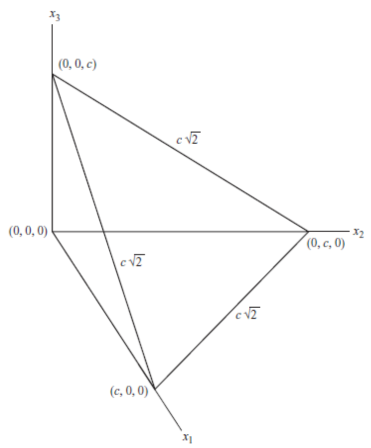

Figure 2: Simplex in 3-Dimensions in the Nelder and Mead algorithm

Source: [8]

Powell [7] developed a method using the idea of conjugate directions defined with respect to the quadratic form. If minimization is carried out along successive directions, which are conjugate with respect to all the previous directions, the convergence can be achieved. Powell developed the idea of constructing the conjugate directions without using derivatives [8].

The concepts of simulated annealing, genetic and differential evolution algorithms also come under the same category. Simulated annealing is a stochastic search method that is analogous to the physical annealing process where an alloy is cooled gradually so that a minimal energy state is achieved. It avoids getting stuck in local optima and keeps track of the overall best objective function value [9].

A genetic algorithm is a technique used to automate the process of searching for an optimal solution. Since it conducts the search from a population of points, the probability of the search getting trapped in a local minimum is limited [10]. Genetic algorithms start searching by randomly sampling within an optimization solution space, and then use stochastic operators to direct a process based on objective function values [11]. Genetic operators control the evolution of successive generations. The three basic steps of reproduction process are selection, crossover and mutation. A genetic algorithm starts by generating a number of possible solutions to a problem, evaluates them and applies the basic genetic operators to the initial population as per the individual fitness of each individual. This process generates a new population with higher average fitness than in the previous step, which in turn will be evaluated. The cycle is repeated for the number of generations specified by the user, which is dependent on the complexity of the problem [10].

Gradient-based strategies are based on the derivatives or gradients of the objective function. Some of the algorithms coming under this category include steepest descent (Cauchy) method, Conjugate gradient (Fletcher-Reeves) method, Newton's method, Marquardt method and Quasi-Newton method [8].

In the steepest descent method as shown in Figure 3, the search starts from an initial trial point and iteratively moves along the steepest descent directions until the optimum point is reached. The convergence technique of the steepest descent method can be greatly improved with the concept of conjugate gradient. Newton's method, which is a very popular method, is based on Taylor's series expansion. Marquardt method is a combination of both the steepest descent algorithm and Newton's method, has the advantages of both the methods in terms of the movement of the function value towards the optimum point and fast convergence rate. Quasi-Newton methods are well known algorithms for finding the optimum of nonlinear functions. However, it should be noted that the aforementioned gradient-based algorithms can only be used for solving unconstrained optimization problems [8].

Similar to genetic algorithms, evolutionary strategies are optimization algorithms that apply the principles of natural evolution as a method to solve parameter optimization problems. The strategy is to apply mutation and selection, alternating on a population or a single solution in order to gradually improve its function value. They are considered to be robust search algorithms that can be used for non-differentiable function optimization [8].

Pareto optimization algorithms are used for handling multi-objective optimization problems. Pareto optimality applies the concept of dominated and non-dominated solutions. A solution is Pareto optimal if it is not dominated by any other solution. In this case the optimization search is formulated as a multi-criteria, or multi-objective, search for a set, or Pareto-optimal front, of optimal solutions. Figure 4 uses one such possible optimization for cost and performance (solutions that are down and to the left are better) to illustrate a Pareto front. A designer, who is presented with such results, then has a range of possible solutions (which are all optimal) that can be utilized for decision making [12].

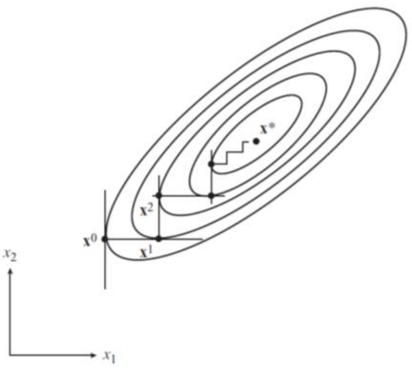

Figure 3: Steepest Descent method
Source: [8]

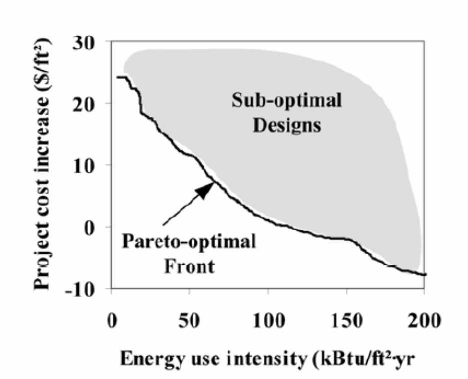

Figure 4: Pareto front of optimal solutions
Source: [12]

The choice of the optimization algorithm is influenced by the characteristics of the optimization problem. Hence the selection of an optimization algorithm depends primarily on the following considerations:

- Structure of the function (linear, non-linear, convex, continuous, number of local minima, etc.)
- Availability of first and second order derivatives
- Size of the problem (number of independent parameters)
- Problem constraints (on the independent parameters and/or the dependent variables)

3. Optimization of Performance of Buildings

Even though the use of mathematical models in building design is relatively new, the application of optimization techniques to various building design problems has been in use for the past 30 years. Such applications range from spatial allocation problems, as well as site developments and land use, to the design of structural and mechanical systems in buildings with different degrees of success [13]. Most optimization problems related to building performance can be formulated as non-linear constrained problems. Furthermore, they are inherently multivariate and multi-criteria problems having typical characteristics. The governing parameters form a mixture of both continuous and discrete variables [13]. Continuous variables are real numbers that may be varied continuously between lower and upper bounds. Building design involves the selection of components that are included in the design. Choosing the best one from different building components is a discrete process. Therefore, variables specifying the selection of building components may be represented by integer values. Many building performance optimization problems are comprised of non-linear relationships with non-differentiable objective functions [13]. Hence, the selection and application of optimization algorithms to building performance analysis has to be done with utmost care. Many different methodologies have been recommended for optimizing the performance of buildings in the literature. This section provides the most recent developments in this area.

An optimization model was established for determining the thermal design of an office building with minimum initial and operating costs [14]. The total discounted cost of the entire heating and insulation process was used as the criterion of optimality.

Design of parallelepiped open plan office buildings was carried out based on multi-criteria optimization, considering thermal load, daylight availability, net usable area and capital cost [15]. Dynamic programming was used for building performance optimization with respect to design variables of window geometry, wall and roof construction, building orientation, massing, floor area and the shape of the building.

A model based on thermal discomfort as the criterion of optimality with a sequential simplex type of search procedure to optimize the thermal performance of buildings under periodic indoor and outdoor design conditions was described using a typical outdoor weather cycle for summer in Australian cities over several design variables [16, 17].

The optimum technology mix was determined for selected building projects [18]. This method considered design parameters such as the shape of the building, orientation, amount of insulation and window areas etc. In order to find the optimum parameter values, this method established a multivariate problem formulation, taking into consideration the total annual cost for the building, as well as the total annual energy consumption. The optimization procedure was comprised of cyclic coordinate search, as well as the Hooke and Jeeves direct search method [4].

Another approach, not only simulated the thermal performance of the building, but also applied numerical optimization techniques to determine the design variables, that optimized the thermal comfort conditions of the building [19]. The method took into account the design variables related to the building envelope and fabric, such as the aspect ratio, building orientation and the glazing ratio etc. This method investigated six different objective functions, which represented six different ways of quantifying the thermal comfort involving decision variables that were subjected to linear constraints. The resulting constrained optimization problem was solved using a combination of the Nelder and Mead simplex method [6], and the complex method described by Mitchell and Kaplan [20].

A direct search optimization coupled to an hourly thermal simulation tool was performed for minimizing the energy consumption for heating and cooling in residential buildings [3].

Dimensions of windows were optimized with the objective of minimizing the energy required for heating and artificial lighting in a building [10]. The optimization was based on the results generated by the building simulation software. The software automatically adjusted the amount of artificial lighting, so that the required illumination level was achieved. This resulted in an unconstrained optimization problem that was solved using genetic algorithms described by Goldberg [11].

The design optimization problem was disintegrated into sub-problems related to the optimization of internal partitions and shape of the building for the ease of coordination of the solution [21]. The shape of the building was represented by design parameters such as wall lengths, number of storeys, window to wall ratio etc. This method was based on a constrained multi-criteria formulation that took building construction costs, seasonal demand for energy for heating, and pollutant levels emitted by heat sources, as objective functions. The optimization problem was solved using a combination of analytical and numerical methods.

Optimum values related to the amount of insulation, type of glazing, window to wall ratio etc. were also determined [22]. This established a constrained optimization problem formulation, where the lifecycle cost of the building was taken as the objective function. In addition, the energy required by the building, the number of hours where overheating occurred and the daylight factors were taken as constraints. The resulting optimization problem consisted of discrete as well as continuous variables. The optimization was done using the simulated annealing method [23] for optimizing the discrete parameters and the method suggested by Hooke and Jeeves [4] for optimizing the continuous variables.

A strategy for optimizing the design and operation of a HVAC system in a building was also described [24]. The decision variables in this case included design parameters such as coil width and height, number of rows and control parameters such as supply air temperature, airflow rate and on/off status of the system. The method adopted a multi-criteria formulation, with the operating cost of the system and the maximum thermal discomfort as objective functions. It made use of the genetic algorithm described by Goldberg [11] for solving the optimization problem.

An optimization technique to set the level of insulation of the building envelope to maximize net energy savings in passive as well as in air-conditioned buildings was suggested [25].

Aspects on green building design were also considered. [26]. It determined the optimum values related to building orientation, aspect ratio, window to wall ratio etc. This method was based on a multi-criteria formulation, with the building life cycle cost and the life cycle environmental impact taken as the objective functions. The optimization problem was solved using the multi-objective genetic algorithm [27]. The method provided the Pareto set for the two objective functions, which could be used for assessing the level of compromise between optimizing economic aspects of the building and optimizing the environmental impact of the building.

Multi-criteria optimization has been applied to optimize the shape of energy-saving buildings. The criteria considered in the optimization were to minimize thermal load, minimize capital cost and to maximize net usable area [21].

It is observed that the aforementioned studies have considered the following design variables for optimizing the performance of buildings

- Building orientation
- Shape of the building expressed in terms of the aspect ratio and number of floors
- Amount of insulation in the building envelope
- Massing
- Construction characteristics of building elements
- Window to wall ratio
- Window type and dimensions
- Amount of glazing
- Design and operation parameters of HVAC systems

The above mentioned studies have used different problem formulations in order to optimize the performance of buildings. Both single and multi-criteria schemes, as well as unconstrained and constrained formulations have been established.

4. Coupling of Building Simulation with Optimization

Whole building energy simulation tools can be coupled with optimization schemes for obtaining the best and most realistic results with minimum time and effort. *GenOpt 3.1.0* [28] is a generic optimization program that serves this purpose. Since one of its main application fields is building energy usage or operation cost optimization, *GenOpt* has been designed in such a way so that it addresses the optimization problems in this area. It can be coupled with any whole building simulation program that reads its input from text files and writes its output to text files. *GenOpt* automatically finds the values of user defined independent variables that minimize the objective function. The independent variables can be continuous variables (possibly with lower and upper bounds), discrete variables or both. Constraints on dependent variables can be implemented using penalty or barrier functions. *GenOpt* initiates the simulation program, checks for possible simulation errors, reads the value of the objective function to be minimized from the simulation output file and then determines the new set of input parameters for the next run. The whole process is repeated iteratively until a minimum of the objective function is achieved. It uses parallel computing to evaluate the simulations [28]. The coupling of *GenOpt* with a whole building simulation program is shown in Figure 5.

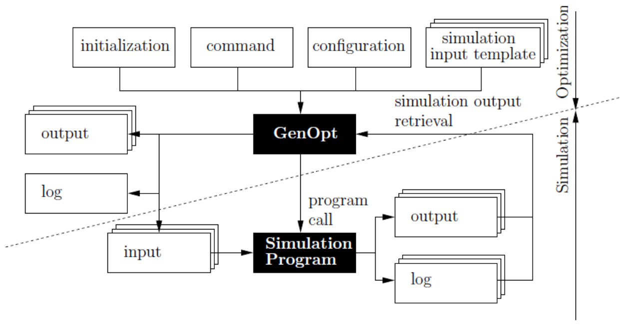

Figure 5: Interface between *GenOpt* and a whole building simulation program
Source: [28]

GenOpt has a library with local and global multi-dimensional and one-dimensional optimization algorithms and algorithms for performing parametric runs. An algorithm interface allows adding new optimization algorithms without knowing the details of the program structure. The platform independence and the general interface make *GenOpt* applicable to a wide range of optimization problems [28].

5. Conclusion

The paper discussed the applicability of existing optimization algorithms for building performance optimization. It is evident from aforementioned studies that it is of much importance to employ appropriate building optimization methodologies to enable the decision makers to optimize the performance of buildings based on selected criteria and to obtain realistic results. According to the previous studies it is observed that direct search optimization methodologies such as Hooke & Jeeves and Nelder & Mead algorithms are the ones most suited for optimizing performance of buildings. Also, genetic algorithms are frequently employed because of their inherent capability to work with complex simulation programs and their proven effectiveness in solving complex problems that cannot be readily solved with other optimization methods. However, gradient-based methods are not well suited for solving whole building optimization problems because of the possibility of the solution getting trapped in local minima.

In addition, the process of generating building performance solutions can be made efficient, accurate and less time consuming, by coupling the whole building energy simulation tool with an appropriate optimization program such as *GenOpt*. *GenOpt* has a library for accommodating different optimization algorithms that the designer can select from.

This paper forms the initial step towards extensive work that could be carried out on optimizing building performance through building envelope elements, involving whole building energy simulation coupled with generic optimization.

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