The application of Differential Evolution to HVAC optimization

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Abstract

We examined the optimum window area, building aspect ratio and building orientation for an apartment building in two different locations: Winnipeg, Canada and Miami Florida. This application was based on a Python script program called the EnergyPlus analysis program and utilized Differential Evolution as the numerical optimization scheme. EnergyPlus is a whole building load and energy analysis program that is well understood and freely available on the internet. It can be used to both size equipment and perform annual energy analysis. It is widely used in the HVAC industry and has demonstrated a good track record. Differential Evolution is a genetic algorithm that is used to numerically find the global optimum of problems that can have continuous, integer, and discreet variables. It uses the existing population in a generation to determine mutation, and is purported to be faster than other genetic algorithms. The annual energy cost was used for the cost function of the optimization.

We will discuss the requirements and issues involved with developing a Python based program called a stand-alone program. Additionally, we will present the results of this exercise as well and present a thorough discussion of the issues and potential pitfalls of this type of exercise.

Keywords: HVAC, optimization, Differential Evolution.

1 Introduction

The energy consumption demands of modern society and limited availability of energy sources has resulted in increasingly stringent building codes. In North America this has resulted in the adoption of standards such as ASHRAE 90.1 [1]

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or similar local requirements. These standards require a minimum energy consumption performance of new construction and for major renovations to existing buildings. This is resulting in greatly improved design and construction methods to meet these standards and in many cases to exceed the standards.

The significance of the energy consumption of buildings becomes very apparent if we examine the energy consumption patterns that are given for the United States. Figure 1 demonstrates the typical split that we see between various sectors as given by the US Energy Information Administration [2]. The typical focus on transportation and the industrial sectors is significant at roughly 60% of total energy consumed, but it is clear that significant improvements in buildings, residential and commercial, must be made if we are to make significant reductions in net societal energy consumption.

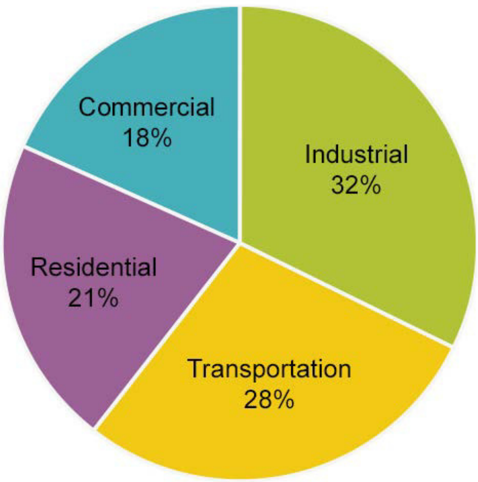

Figure 1: US Energy consumption by sector, 2012 [2].

This has resulted in an interest in developing methods of optimum design to meet these goals. Additionally, major industry associations, such as ASHRAE, are developing research objectives to develop both the tools and understanding to allow engineers to optimize the design of a building [3]. It is to this end that the research reported here was undertaken.

2 HVAC optimization

HVAC optimization is in many ways identical to a typical optimization project. The steps are readily understood.

First we must be able to quantify what it is we want to optimize, or equivalently develop a cost function. In general this is not as simple as it may first appear. Several cost functions for HVAC design are legitimate cost functions. For example, one can simply consider the capital cost of equipment

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and construction. This will result in an inexpensive system to purchase, but could result in high operating costs. One could use energy consumption rates. This would minimize the operating costs but could result in substantial penalties due to capital costs. There are many other possible cost functions that can be selected. The main thought that has to be kept in mind is that the cost function will have a strong influence on the resulting optimum design. The selection of the function depends on factors outside of the mathematics or engineering of the design.

The next consideration is how to determine the value of the cost function for a particular design. This is done using a building energy modelling code for HVAC work. These codes have been developed to a fairly reliable state over the last few decades. There is a good base of understanding of the performance of most of the available codes. It should be noted however that some of the codes are very specific in nature and may miss certain issues.

The final step is to apply some form of numerical optimization algorithm to obtain the optimum design. These methods can be local hill climbing methods that produce improved performance, or genetic based methods that search for a global optimum. Of the three steps for HVAC optimization, the numerical optimization algorithms are the best developed even though some issues are still under development.

The work discussed in this paper is based on Ms. Guenther's undergraduate thesis [4]. It can be obtained in electronic form from the first author upon request.

The following sections will discuss the specific features employed in this work.

2.1 Building energy modelling

The building energy modelling code is essential to determine the energy usage and cost of a particular design that will be required for optimization. The main requirements are that the code be reliable and fairly easy to use. Additionally, the program must be able to be run without human intervention as the optimization code will require tens, hundreds, and possible thousands of simulations.

These codes deal with very sophisticated and complex building structures, with numerous components. It is a daunting task to develop an in-house code for one's individual use due to the sheer scale of the coding required and the significant effort at testing required. Hence, it is best to utilize an existing code that has been thoroughly tested and has an established base of users.

The importance of reliable building energy modelling to the development of high performance buildings has led to a significant effort in developing software tools. Several existing commercial codes are available for a fee from Carrier and Trane which are used extensively in industry. Several codes are available for free from the web. The earliest free code is DOE-2 [5], it is available for free from the US Department of Energy upon registration. This code was written a in an old coding style and is a challenge for most users. A graphical user interface, eQuest, was developed to simplify DOE-2's use. This is a very good, reliable platform, which unfortunately is not suitable for optimization use as it is a graphical user based code that requires human intervention to execute a simulation.

The code selected was EnergyPlus [6]. It is a thoroughly tested and well established product that is available for download free, and has the advantage of being able to be run in a stand-alone, non-GUI mode which was ideal for this project. EnergyPlus has a widely used user base and is reported to be both reliable and accurate.

2.2 The objective function

The objective function used for this work was the annual energy consumption computed by EnergyPlus. The EnergyPlus program uses extensive input files that contain all of the data required to model a building: building layout, construction details, mechanical equipment used, and so on. The number of variables used to define a building is very extensive and includes all of its details. Additionally, a weather file must be specified that details the annual environmental conditions that the building will experience. EnergyPlus can then determine the entire energy consumption on a monthly and annual basis by determining heat loss through the exterior surfaces and heat and moisture loads due to infiltration. There is no single mathematical formula to do these calculations but rather a set of evaluations that must be combined to determine the energy consumption. This information is readily found in the EnergyPlus output files. Mathematically, we recognize that the net energy consumed is a function of the design variables, i.e.

$$O = F(\alpha, AR, G_1, G_2).$$

where O is the net energy consumed by the building, α is the building orientation, AR is the aspect ratio of the rectangular building floor plan area, G_1 is the percentage of glazing on the north and south faces of the building, and G_2 is the corresponding percentage of glazing on the east and west faces of the building.

The relative fitness of two competing potential members of a generation is determined by which the lowest net energy consumption as determined by EnergyPlus had, and hence moved on to the next generation.

2.3 Python scripting

Traditionally, one would think of developing an optimization program based on traditional coding languages such as C or Fortran. This requires all of the components necessary to be able to be run as subroutines. This is not possible if one wishes to use an established code such as EnergyPlus. Essentially, the energy modelling code can only be run from a command line or Windows. It was felt that attempting to develop an interface that would run EnergyPlus would be too difficult, and that we elected to use a scripting language, in this case Python.

Langtengen [7] provides an excellent discussion of the Python scripting language. The main features that are of value to this work are: it allows external programs to be executed as if a command line is used; it has excellent capabilities in opening, manipulating and closing text files; and it allows for significant programming capabilities.

The means of communicating with EnergyPlus was by manipulating the standard input and output files that it created. New generations were created by changing the relevant portions of EnergyPlus's input files. The performance of a population member was then obtained by running EnergyPlus with its input files and examining the resulting output files for the relevant data.

It should be pointed out that this is not a particularly fast process. Opening and manipulating files requires a significant amount of computer overhead. Anyone wishing to develop a production code should strongly consider either cooperating with the energy modelling code developers or write their own.

2.4 Differential Evolution

The selection of numerical optimization algorithms is an important issue in the development of an optimization scheme. The well-known hill-climbing methods are known to be very rapid; however, they are known to trap at the nearest local maxima. To find the global maximum one needs to restart the search from many initial positions. This process does not guarantee that the global maximum has been found. This process favours problems that have well known, and relatively simple solution space. Global maximization is the purview of genetic algorithms. These methods are statistical based searches of the solution space, and can deal with non-differentiable problem parameters. The main concern is that they tend to be very computationally intense and hence slow to converge.

Differential Evolution (DE), a genetic algorithm, was chosen for this work. DE is a well-established genetic algorithm used for numerical optimization. Its key feature is that it uses the current population to advance the solution which makes it converge more rapidly than most other genetic optimization algorithms. The basic process of DE is shown in the Figure 2. Here an initial population is generated by randomly distributing population members throughout the solution space. The initial population members are then evaluated to determine their individual fitness, in this case energy consumption. At this point a new generation is formed. This is done for each population member. A child member is created from the parent by mixing the parameters with another, randomly selected, member of the population through a cross-over process. A mutation process is also applied to the child based on two additional, randomly selected population members. The child's fitness is then determined and the fittest of the child or the parent is passed to a new generation. This process is continued over a number of generations until it converges. The details of DE are discussed by Price [8].

The authors have had considerable experience with DE and have selected it based on many satisfactory projects. It is easy to use and code. Additionally, a Python based implementation by Storn [9] exists and was used in this project.

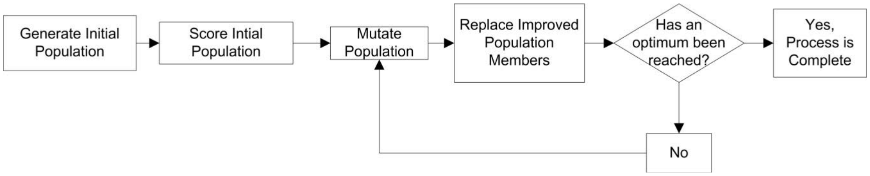

Figure 2: Simplified optimization flow chart.

3 Test cases

Two test cases were examined for this work, both based on the same basic building configuration. Case one was based in a northern climate, Winnipeg, Canada that has a dominant heating load and modest cooling requirements. The other based on a more tropical climate, Miami, U.S., which as a dominant cooling load and modest heating requirements.

The basic building type is a three story apartment building with four apartments on each floor separated by a common hallway as shown in Figure 3. The exterior walls and roof had insulation levels set to the local minimum building code requirements. The four parameters examined were the building orientation, the overall building aspect ratio, and the percentage of glazing on the east and west, and north and south exterior walls.

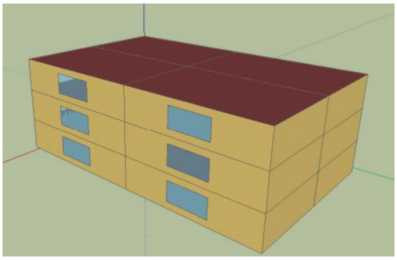

Figure 3: EnergyPlus Building model, AR=1.6.

3.1 Test case design variables and constraints

EnergyPlus, as all other energy modelling codes, utilize an extensive list of pre-defined variables that specify the building that is being modelled. These details are usually given in lengthy input files due to the sheer number of variables that can be specified. The specific details of the input files are program dependent but their overall characteristics are the same. For example the orientation of the building is given as it influences the solar load on the building. The physical shape and size of the building is also necessary. Characteristics of walls can be given through construction details or overall thermal resistance. The location and size of all windows and doors are necessary or a percentage of overall glazing can be specified. As one can imagine, the number of variables possible for a building is large and far too extensive for an optimization study at this time.

The structure of the test cases was influenced heavily by the current research in the field. This project had to balance the possible amount of detail produced with the challenges that arose and the limitations and time constraints of this project. year. The main aspects that needed to be defined were the building itself, the variables being optimized and their acceptable ranges, and the locations for the test cases.

The building itself was a three-story, 12-suite, symmetric apartment building. The selection of the variables of the building that were optimized was influenced heavily on the article "Using Passive Design" [10], resulting in the following parameters being optimized: building orientation, building aspect ratio, and wall to window ratio for the North/South and East/West sides.

The variables used for this project were adjusted within the input files to create both the parent and child members that were examined. The Python code read and adjusted the input files to create child members as well as read the output files to determine the net energy consumed.

3.2 Variable constraints

Within these variables, it was important to restrict the possible ranges of solutions to those that would yield building designs that were practical for construction. As the building was symmetric, the orientation was constrained to a 180° range. This restriction helped to narrow the solution space, which sped up convergence and reduced the chance that the code would "bounce" between two equal minima 180° apart. The most appropriate range to ensure convergence was found to depend on the primary conditioning mode of the building. Modifying the building shape was complicated due to the number of surfaces involved in defining the building, so the aspect ratio variability was restricted to 2 significant figures between 1.0 and 1.7 (i.e. 1.0, 1.1, 1.2 ... 1.7). Lastly, the window to wall ratio was restricted to a range of 9–60% window coverage. The upper bound of the window to wall ratio was specified by the Canadian National Building Code [11], and the lower bound was specified by practicality: the code often converged to the minimum allowable window percentage, and the intent was for the resulting building to still be desirable for inhabitants.

3.3 Winnipeg

Winnipeg is located at 49.92N 97.23W and 239m above sea level. It is characterized by having its dry bulb 99% heating outside temperature being −29.9°C. During the summer the 2% outside dry bulb cooling temperature is 27.2°C with a mean coincident wet bulb temperature of 19.4°C. These conditions were obtained from the ASHRAE Fundamentals Handbook [12].

The overall characteristic of Winnipeg is that it has a cold winter temperature with relatively mild summer temperatures. The climate is relatively dry.

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3.4 Miami

The corresponding data for Miami are Miami is located at 25.82N 80.43W and 9m above sea level. It is characterized by having its dry bulb 99% heating outside temperature being 10.9°C. During the summer the 2% outside dry bulb cooling temperature is 32.1°C with a mean coincident wet bulb temperature of 25.2°C. These conditions were obtained from the ASHRAE Fundamentals Handbook [12].

The overall characteristic of Miami is that it has warm winter temperature with hot summer temperatures. The climate is relatively moist.

4 Results

4.1 Winnipeg

The simulation case run in Winnipeg was allowed to run for 50 generations. The resultant population had a mean score of 350.30 GJ and minimum score of 350.22 GJ, with a difference of 0.080 between the two. This optimization run took approximately 48 hours to complete on a Pentium 4 computer.

The parameters that resulted in the optimum performance are given in Table 1, and the design is shown in Figure 4.

Table 1: The parameters that resulted in the best configuration in Winnipeg.

Orientation (°)	Aspect Ratio	N/S Window	EW Window	Score (GJ)
114	1.0	9.00%	9.00%	350.22

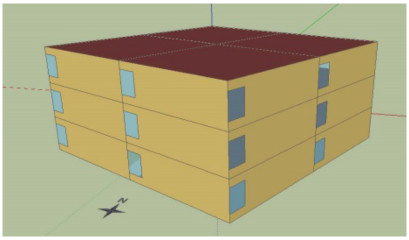

Figure 4: Best design for Case 1, 50 generations.

4.2 Miami

The test case in Miami was also allowed to run for 50 generations. The results show a mean score of 513.30 GJ and minimum score of 512.99 GJ, for a difference of 0.31 GJ. This optimization run took approximately 114 hours to complete on a Pentium 4 computer.

The parameters that resulted in the optimum performance are given in Table 2, and the design is shown in Figure 5.

Table 2: The parameters that resulted in the best configuration in Miami.

Orientation (°)	Aspect Ratio	NS Window %	EW Window %	Score (GJ)
192	1.0	9.16%	9.15%	512.99

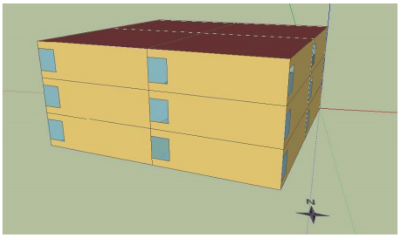

Figure 5: Best design for Case 2, 50 generations.

5 Discussion

The objective of this works was to demonstrate the use of the differential evolution optimization algorithm as a design tool for reducing building energy consumption

For this project, two test cases were examined. One was in Winnipeg, Canada, and other was in Miami, FL. The cost function used as the minimization target for the algorithm was the total site energy usage of the building. For each of the test cases, the final results for the cost function used were logical when examined using heat transfer principles. These results demonstrated clear trends in variable selection for optimum building design in different locations, which is the intended result when carrying out differential evolution optimization of a sample building.

In this project, the four variables examined for optimization were the degree of orientation, aspect ratio and window to wall ratio (on north/south and east/west sides). The results obtained showed that the optimum degree of orientation differed depending on the primary mode of conditioning the building. When heating is the primary mode, the optimum configuration was full south exposure on the longest side of the building, increasing solar gains and reducing the heating load. When cooling is the primary mode, the optimum configuration was south exposure on the shortest side of the building, reducing solar gains and reducing the cooling load. For both cases, the optimum building aspect ratio and wall to window ratio was that which minimized the heat transfer occurring through the building envelope: minimum aspect ratio (1.0) and window to wall ratio (9%), minimizing the surface area for heat transfer and maximizing the overall insulation value of the wall. Reducing the heat lost or gained through the envelope reduced the energy consumption required to condition the building, minimizing the cost function.

These results are useful; however it became clear throughout the process of developing this project that the process was as important as the results. Challenges arose throughout the process of integrating the differential evolution code and building simulation software to produce meaningful results, requiring diligence, decision-making and project management to overcome them and successfully complete the project. These sorts of challenges will also arise as this technique is developed further. Optimization techniques that take a prohibitively long time or require too much specialized knowledge are unlikely to be readily useful in industry. As the focus of this project was to match ASHRAE's industry priorities of incorporating optimization into the HVAC design process [3], industry relevance was very important.

Though the code in its current form requires significant development before it is at this level of usability, the positive results that can be obtained by the process are demonstrable. With further development to increase the efficiency of the code and streamline the process, software utilizing this algorithm could become a very helpful tool for designers looking to optimize a particular aspect of a new design. Development in the area of user interface and input flexibility would allow for more comprehensive optimization criteria to be used when desired, and the ability to focus in on a particular metric (i.e. passive heat gain) if that is the particular concern.

It should be pointed out that that while the results are valid within the scope of this project, some important issues need to be addressed. It is clear, that if all we wish to accomplish is the reduction of the heating, ventilating, and air conditioning energy consumption we should eliminate glazing and make all of our buildings have a square floor plan. This will minimize our thermal losses. Unfortunately, this will not reduce the building's net energy consumption as several other non-HVAC consumption sources will be neglected. The split on typical building energy consumption is given in Table 3, as stated by Crawley [13]. It is clear that while HVAC energy consumption is significant at 30.5%, other factors also play a significant role in net energy consumption. The high cost of lighting will certainly work against zero glazing and needs to be factored

Table 3: Typical building energy consumption in the US [13].

Lighting	17.1 %	Office Equip.	4.7 %
Space Heating	13.3 %	Water Heating	4.2 %
Ventilation	8.8 %	Computers	3.3 %
Space Cooling	8.4 %	Other Uses	32.3 %
Refrigeration	6.3 %		

into any net building optimization exercise if meaningful savings on energy consumption are to be achieved. The other sources of consumption were not considered in this work.

6 Conclusions

In conclusion, the results obtained by this project provide useful data for the field of building HVAC system optimization. Optimum design ranges were achieved for four different test cases using the differential evolution algorithm, demonstrating that this could be a very useful technique to incorporate into HVAC design. Development to introduce optimization as an industry tool in HVAC design will increase the energy efficiency and reduce the energy consumption of buildings, which is important to building owners and designers. The results produced by this project and the conclusions that can be drawn for them will be a relevant inclusion into the field of HVAC system optimization literature.

Additionally, it is very clear that all of the sources of energy consumption must be factored into any optimization project if we are to obtain meaningful energy reductions and ultimately to design high performance buildings.

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