TESTING THE IMPACT OF USING CUMULATIVE DATA WITH GENETIC ALGORITHMS FOR THE ANALYSIS OF BUILDING ENERGY PERFORMANCE AND MATERIAL COST

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TESTING THE IMPACT OF USING CUMULATIVE DATA WITH GENETIC ALGORITHMS FOR THE ANALYSIS OF BUILDING ENERGY PERFORMANCE AND MATERIAL COST

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Nomenclature

AEC: Architecture, Engineering, and Construction

AIA: American Institute of Architects

ASHRAE: American Society of Heating, Refrigerating and Air Conditioning Engineers

BEM: Building Energy Model

BEP: Building Energy Performance

BIM: Building Information Modeling

BOM: Building Operation Modeling

BTU: British Thermal Unit

CBECS: Commercial Building Energy Consumption Survey

DOE: Department of Energy

DPM: Design Performance Modeling

EA: Evolutionary Algorithm

EPA: United States Environmental Protection Agency

EUI: Energy Use Intensity

GA: Genetic Algorithm

GDP: Gross Domestic Product

GHG: Greenhouse Gas

IFC: Industry Foundation Class file format

kBTU: Kilo British Thermal Unit (1,000 BTU's)

LCA: Life Cycle Analysis

LCC: Life Cycle Cost

m^2: Square meters

MOGA: Multi-Objective Genetic Algorithm

NREL: National Renewable Energy Laboratory

PRM: Project Resource Modeling

RSI: R-Value in SI (metric) units

SC: Shading Coefficient

SF, ft^2: Square feet

SHGC: Solar Heat Gain Coefficient

SI: International System of Units

T_{sol}: Solar Transmittance

T_{vis}, VT: Visual Transmittance

US: United States of America

USGBC: United States Green Building Council

Summary

The demand for energy and cost efficient buildings has made architects and contractors more aware of the resources consumed by the built environment. While the actual economic and environmental costs of future construction can never be completely predicted, energy simulations and cost modeling have become accepted ways to guide the design and construction process by comparing possible outcomes. These tools are now commonplace in the construction industry, and researchers are continuing to develop new and innovative strategies to optimize building design and construction. Previous research has proven that genetic algorithms are effective methods to evaluate and optimize building design in situations that contain a large number of possible solutions. The technique makes a computationally difficult multi-optimization process possible but is still a reactive and time consuming process that focuses on evaluation rather than solution generation.

This research presented in this paper builds upon established multi-objective optimization techniques that use an energy simulator to estimate a conceptual building's energy use as well as construction cost. The study compares simulations of a simplified model of a 3-story inpatient hospital located in Atlanta, Georgia using a defined set of variables. A combined global minimum of annual energy consumption and total construction is sought after using a method that utilizes a genetic algorithm.

The second phase of this research uses a modified approach that combines the traditional genetic algorithm with a seeding method that utilizes previous results. A new set of simulations were established that duplicates the initial trials using a slightly

modified set of design variables. The simulation was altered, and the phase one trials were utilized as the first generation of simulated solutions.

The objective of this thesis is to explore one method of making energy use and cost estimating more accessible to the construction industry by combining simulation optimization and indexing. The results indicate that this study's proposed augmented approach has potential benefits to building design optimization, although more research is required to validate this hypothesis in its entirety. This study concludes that the proposed approach can potentially reduce the time needed for individual optimization exercises by creating a cumulative, robust catalog of previous computations that will inform and seed future analyses.

The research was conducted in five general stages. The first part defines the research problem and scope of research to be conducted. In the second part, the concepts of genetic algorithms and energy simulation are explored in a comprehensive literature review. The remaining parts explain the trial simulations performed in this study. Part three explains the experiment's methodology, and part four describes the simulation results. The fifth and final part looks at what the possible conclusions that can be made from analyzing the study's results.

CHAPTER 1: INTRODUCTION

1.1. Research Motivation

Buildings, both during their construction phase and occupancy lifecycle, consume a large amount of both monetary resources and natural resources. In the US alone, "the design, construction, and operation of buildings account for 20 percent of U.S. economic activity and more than 40 percent of energy used and pollution generated" (US Green Building Council, 2003). However, this trend cannot continue, and buildings will need to drastically reduce their energy emissions in the near future. To combat the environmental degradation caused by buildings, organizations and governments worldwide are imposing regulations that reduce building energy use and emissions drastically.

The 2030 Challenge is one such program that requires incremental reductions in fossil fuel energy in buildings every five years, with the ultimate goal of carbon-neutral buildings by the year 2030. In 2007, a law passed requiring all new US federal buildings and major renovations to meet the energy performance standards of the 2030 Challenge, and a bill has been recently introduced in Congress that contains a stricter national building energy code shaped by the challenge. In addition, the 2030 Challenge has officially been adopted by "The National Governors Association, The National Association of Counties, International Council for Local Environmental Initiatives, the states of Minnesota, Illinois, New Mexico, Washington State, and numerous cities and counties," and similar measures have been put into law in

California, Ohio, Oregon, and Vermont (Architecture 2030, 2012). This movement is not confined to the United States. The European Commission also has official plans for a European Union energy policy that reduces greenhouse gas emissions 20% by the year 2020 (Hamdy, Hasan, & Siren, 2011).

While environmental standards are increasing, there is also increasing pressure for building construction to be more cost-effective. Construction accounts for a sizeable portion on the economy. According to the US Department of Commerce, the total construction market in 2008 was $1.8 trillion and accounted for 13.4% of the $13.2 trillion U.S. GDP. That same year, new commercial and residential building construction constituted 6.1% of the GDP alone (US Green Building Council, 2012). Yet the amount spent on the construction industry is highly impacted by the state of the economy as a whole. Reed Construction Data compiled the Department of Commerce statistics and found that the total annual US construction spending decreased 7.4% in 2008, decreased 15% in 1009, and further decreased 11% in 2010 (Markstein, 2011).

Another measure of the construction industry is the Architecture Billings Index (ABI), a measurement compiled by the American Institute of Architects (AIA) Economics and Market Research Group. The ABI is a diffusion index derived from a monthly survey that "is a useful leading indicator of future levels of nonresidential construction activity" (Baker & Diego, 2005). More specifically, the ABI provides approximately a nine to twelve month "glimpse into the future of nonresidential construction spending activity." From May 2011 to May 2012, the ABI was showing construction decline for six months and growth for seven months (American Institute of Architects, 2012). In essence, the ABI has indicated that the near future of the construction economy continues to be unstable. In these circumstances, it is reasonable to assess that construction projects need to be cost-effective and economical in order to be built.

The combined circumstances of environmental awareness and economic fluctuation create a vast necessity for buildings to be both cost-efficient and energy efficient, and optimizing these two objectives of building construction is perhaps the most crucial task for the construction industry.

1.2. Problem Definition

The demand for high performance, low cost buildings necessitates an efficient way of evaluating potential construction. Conceivably, every un-built construction project has an unlimited number of possible configurations, which is defined as the "design problem." Every identified scheme that satisfies the project's requirements can be considered a solution to that particular problem. During the design phase of a project, architects, engineers, contractors, and owners make numerous design decisions that significantly narrow the amount of solutions considered. Still, there are still typically large amounts of solutions that are acceptable. The ultimate solution can either be selected arbitrarily or by using a scientific-based method of evaluation. Previous research has shown that optimization techniques using energy simulation tools can be effective in exploring the set of possible solutions (Wright, Loosemore, & Famani, 2002).

The practice of evaluating solutions using energy simulation, however, takes a large amount of set up and computation time. The drawbacks of these methods limit the usefulness of utilizing such techniques on a large scale across the construction industry.

These pitfalls are examined more in depth in Chapter 2 literature review portion of this research.

Therefore, the general research problem statement of this thesis is: "Can an iterative process be outlined in a way that would make a first cost material and energy trade-off analysis tool capable of facilitating the generation of solutions in addition to evaluating solutions?"

Given this objective, the research problem is defined as finding a process that can efficiently and effectively evaluate cost and energy optimization at a pace that stays relevant throughout the design and construction phases of a project. In this way, a multi-objective optimization method can potential inform building design and construction in an interactive manner.

The obvious way to create a faster optimization method capable of keeping pace with real-world construction decision-making would involve developing a less time consuming and more efficient optimization tool. Many previous researchers have already focused on making more efficient optimization using genetic algorithms (Dreo, Petrowski, Siarry, & Taillard, 2005). Some of these methods will also be examined in the Chapter 2 literature review portion of this paper.

The research proposed in this thesis builds upon those foundations and suggests one more augmentation. Traditionally, each multi-objective optimization study that uses genetic algorithms begins with a random sampling of possible solutions, generically called the *population*. This thesis proposes a specific method of initializing an optimization exercise by utilizing past trials for the initial population of a new optimization trial, regardless of whether the trials have exactly similar parameters or variables. The hypothesis of this research is that multi-objective optimization will come at a faster rate when trials are used cumulatively. Alternatively, if unsuccessful, this method will prove to not be a faster way than traditional genetic algorithms to uncover optimal solutions or will fail to uncover optimal solutions all together.

1.3. Project Scope

To test the overall premise of this thesis argument, a specific study needed to be created. This section outlines the overall scope of research including optimization goals, overall parameters, variables, constants, and general constraints. The actual values used in the study are outlined in detail in the methodology chapter of this research.

A hypothetical test building located in the climate of Atlanta, Georgia was used for the purposes of this study. The building function is modeled after patient bed unit wing of an inpatient healthcare facility. The building was modeled as a generic building mass consisting of three-stories, with dimensions related to the standard modules of an inpatient hospital. Generically, the size of hospital developed for the energy model related approximately to a 100-bed inpatient facility. Each story was comprised of five zones, one for each perimeter wall, and one central zone.

The two optimization goals focused on material cost and building energy use. The specific fitness objectives used are estimated initial material cost per conditioned area and simulated yearly energy use per conditioned area. Five variables of building orientation and percent glazing were parametric and tested for optimization.

In all, four trials were conducted to analyze the research hypothesis: one trial established the study, two trials were conducted as controls, and a final trial was used to test the research hypothesis. This process is shown in Figure 1.1, where Steps 1 and 2 perform the first three trials utilizing the traditional approach as outlined in the literature review. Step 3 performs the augmented approach as proposed in this research. Step 4 is the comparison of the trial results.

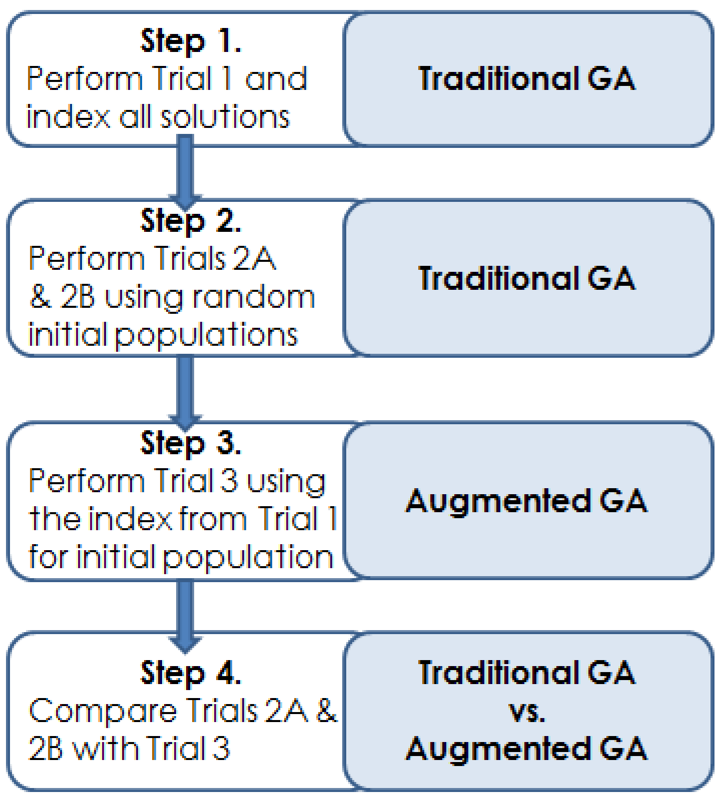

Figure 1.1. Research Process

The remaining properties of this hypothetical building were based on a combination of assumptions and the author's experience as a professional architect. Generally, the majority of the building's properties such as location, building massing, and building type are considered not relevant to the research as they remained the same values for both the control and test trials. These constants are therefore only important in that they remained a neutral base used to measure the effectiveness of the two optimization methods used in the study.

However, the values used in this research still strived to be accurate in order to provide a realistic background for the study. Also, the use of practical parameters was utilized in order to demonstrate the possible applicability of this research in a real-world situation. A healthcare building was chosen due to the high energy use and critical nature of that building subsector, and the Atlanta climate was chosen based on the location of the research. In truth, the specifics are arbitrary but needed to be specified for a complete energy simulation. Refer to Table 1.1 for a brief description of how each trial's parameters differed from one another. These parameters are described in full in the methodology section of this thesis.

Table 1.1. Description of Trials Proposed in Current Research

Trial Run(s)	**Description**
Trial 1	Single Pane Glazing Random initial population
Trials 2A & 2B	Double Pane Glazing Random initial population
Trial 3	Double Pane Glazing Seeded initial population

CHAPTER 2: BACKGROUND & LITERATURE REVIEW

2.1 Introduction to Energy Analysis

The recent demand for energy efficient buildings has made energy analysis a well-researched tool for finding optimal building design solutions. While energy analysis alone will not save the environment, it can be used as an integral tool in combatting the enormous energy strain caused by building and construction. One study looking at the energy use and carbon dioxide implications for residential homes in New Zealand articulated this point: "The global key to reducing carbon dioxide emissions to the atmosphere is the use of renewable clean energy. Until this becomes economically feasible, the short-to-medium-term response is to reduce energy use and increase energy efficiency" (Buchanan & Honey, 1994).

This section provides an overview of why energy analysis has gained popularity, how energy analysis is currently being used in the construction industry, and the effect of Building Information Modeling (BIM) on energy analysis. The final part of this section reviews some of the challenges that building energy analysis faces.

2.1.1. The Demand for Energy Efficient Buildings

Buildings account for a great deal of energy consumption and pollution around the world. The design, construction, and operation of building account for more than 40 percent of energy consumption and pollution in the US (US Green Building Council, 2003). This trend has gained the attention of architects, builders, and owners as well as politicians, developers, and the general public. Metrics have been put in place to measure and reduce the amount of energy used and emissions emitted for building construction and operation around the globe. The ambition to reduce the harmful environmental impacts of buildings is taking place in many countries and across multiple building sectors.

US Buildings

As stated in the Research Motivation section of this paper, new regulations that control the use of fossil fuels are becoming commonplace in the United States. A 2007 law requires all federal buildings to meet certain energy performance standards, and similar regulations are taking into effect in jurisdictions across the country on the municipal, state, and regional level (Architecture 2030, 2012).

International Buildings

This movement spans the globe. A few years ago, the United Nations held a conference in Copenhagen, Denmark called the 2009 United Nations Climate Change Conference, regularly referred to as the Copenhagen Summit. This conference negotiated an international agreement based on six key messages presented by the Sustainable United Nations (SUN) and the United Environmental Program Sustainable Buildings and Climate Initiative (UNEP-SBCI). The six points addressed were summarized in a paper by Bernardes et al (2011) and are as follows:

1. The building sector has the most potential for delivering significant and cost-effective GHG emission reductions;

2. Countries will not meet emission reduction targets without supporting energy efficiency gains in the building sector;

3. The building industry is committed to action and in many countries is already playing a leading role;

4. Significant co-benefits including employment will be created by policies that encourage energy efficient and low-emission building activity;

5. Failure to encourage energy-efficiency and low-carbon when building new or retrofitting will lock countries into the disadvantages of poor performing buildings for decades.

In December of 2009, the Copenhagen Accord was drafted by multiple countries including the United States, China, India, Brazil, and South Africa (Bernardes, Benetto, Marvuglia, & Koster, 2011). While the Copenhagen Accord in a major international agreement, the effect of energy consciousness can be seen in smaller ways around the world as well.

Hospital Energy Use

This current study is proposing the energy analysis of a hypothetical inpatient hospital located in Atlanta, Georgia. Hospitals, as part of the greater commercial building sector, make up a large portion of energy used in building construction and operations. "The commercial building sector is responsible for 18% of US energy use and is the fastest growing demand sector." A Energy Information Agency 2007 report projected that commercial energy consumption would grow by 1.5% per year (Griffith, et al., 2008).

Healthcare buildings, in particular, have a challenge to reduce energy consumption. "Healthcare buildings are the second most energy-intensive building type" (Burpee & Loveland, 2010). In 2003, US healthcare facilities used 594 trillion Btu. This accounted for 9% of all building energy use that year. As a portion of transportation, industrial, and building sectors combined, healthcare buildings accounted for 4% in the US, and approximately 1% of energy consumption worldwide.

2.1.2. Traditional Approaches to Energy Analysis

There are multiple approaches to building energy modeling (BEM) and no concrete methodology agreed upon by the construction industry. A recent energy modeling guide published by the American Institute of Architects (AIA) recommends developing energy models for all building design projects and outlines the following rules of thumb: decide whether energy modeling is appropriate, integrate energy modeling early in the process, develop a smart work plan, set performance goals and benchmarks, identify constraints, balance performance indicators, explore synergies, explore passive systems, eliminate unnecessary systems, compare alternatives, and illustrate your analysis (AIA, 2012).

As these broad steps suggest, the AIA guide proposes no in depth processes to achieve these goals, and only generic summaries are provided for each category. Table 2.1 is a table from that literature that summarizes the benefits and goals of energy modeling during each phase of a design and construction project.

Table 2.1. Broad Energy Goals & Benefits
extracted from (AIA, 2012)

	CONCEPT DESIGN	SCHEMATIC DESIGN	DESIGN DEVELOPMENT	CONSTRUCTION DOCUMENTS	CONSTRUCTION/ POST-OCCUPANCY
TEAM GOALS	Use early Design Performance Modeling to help define the goals of the project (NOTE: Design Performance modeling could be with either component modeling tools or a basic building energy model, but should at this stage address other performance parameters in addition to energy.) Define the project requirements, as informed by modeling results	Review financial and performance energy information from model to guide design decisions	Review design alternatives based on initial goals, as informed by modeling results Create baseline and alternatives to choose from	Create documentation needed to accompany energy model results for code compliance Create documentation needed to accompany energy model results for commissioning and metering/ monitoring validation	Use results of the as-built model for commissioning Compare results of the as-built model against metered data to look for operating problems
ENERGY MODELING GOALS	Experiment with building siting and orientation Determine effective envelope constructions Assess the effects of daylighting and other passive strategies Explore ways to reduce loads	Create a rough baseline energy model Test energy efficiency measures to determine the lowest possible energy use Set up thermal zones and HVAC options	Create proposed models with system alternatives to choose from Refine, add detail, and modify the models, as needed Provide annual energy use charts and other performance metrics for baseline vs proposed Evaluate specific products for project Test control strategies Do quality control check on the models	Complete the final design model Do quality control check on the models Create final results documentation needed to submit for code compliance	Complete the as-built model with installed component cut-sheet performance values Collect metered operating data to create a calibrated model to share with outcome-based database
BENEFITS TO CLIENT	Get entire design team united around project goals Use modeling results to make design decisions informed by integrated system performance	Test different options before implementing them Determine the most efficient and cost effective solutions	Determine the most efficient and cost effective solutions Size mechanical equipment correctly	Use energy model as part of LEED or other sustainable design certification application Provide ability to better predict energy use in the building	Provide ability to refine operations to meet reduced energy use goals in the built project

To gain an understanding how energy analysis simulation is used in current design practice, the researcher conducted an interview with the energy simulation coordinator at a large US-based architectural firm (Wolfe, 2012). The firm that he works at specializes in hospitality, sports, and healthcare architecture, with roughly 1,200 employees in twenty-nine worldwide office. Twenty-two of those offices are located in the United States. A large architecture firm such as this one has a dedicated sustainability department which handles all energy analysis simulation and data.

For ease of comparison, the design firm focuses on one metric that indicates energy use of a building normalized by building size. This metric is typical for demonstrated annual building energy use and is called Energy Use Index, or EUI. “The EUI for a building is the total amount of energy used by the building, most commonly electricity and natural gas, per square foot of floor area, metered on an annual basis. Buildings’ EUI are often reported in units of KBtu/SF/Year. This is a way of comparing different buildings to each other, much like comparing different cars to each other using a miles per gallon rating” (Burpee & Loveland, 2010).

For a usual project designed at the firm where the interviewed sustainability coordinator worked, the EUI is calculated and compared in four different ways: 1) existing building performance based on region and/or building type, 2) baseline simulations using code minimum standards, 3) simulations based on proposed building geometry and materials, and finally, 4) actual post-occupancy data (Wolfe, 2012). Figure 2.1 diagrams these four steps and shows which building phase each is loosely associated with.

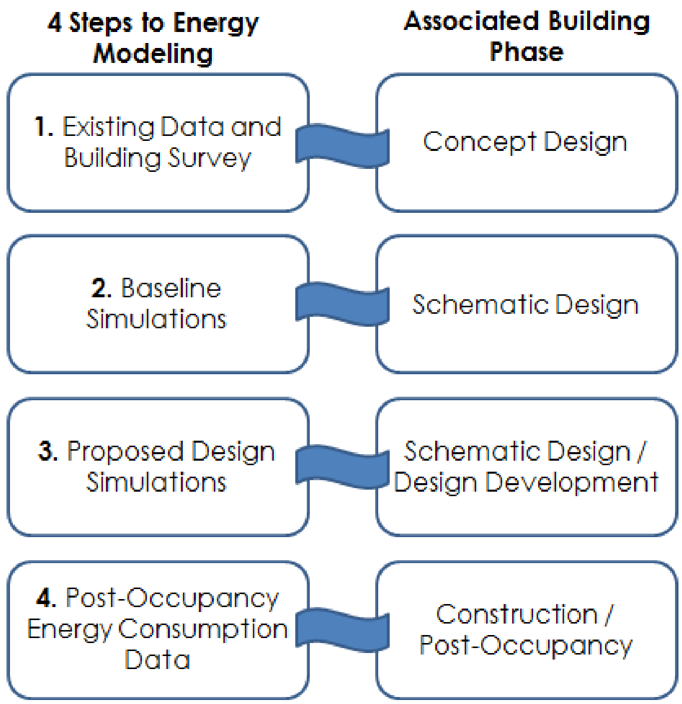

Figure 2.1. Current Steps in the Practice of Energy Modeling

The four energy consumption methods occur chronologically as the building design begins, becomes solidified, and is completed. Figure 2.2 below is taken from the AIA Energy Modeling Guide (2012) and is an illustration of how the first three steps of this process can be compared. The pie charts shown represent steps one, two, and three from left to right. The largest pie chart shows the EUI and energy break down of an existing building (Step 1). The middle pie chart then shows an estimated baseline of an addition to that building using minimum code requirements (Step 2). The final and smallest pie chart represents a possible energy use estimation of the proposed design solution (Step 3).

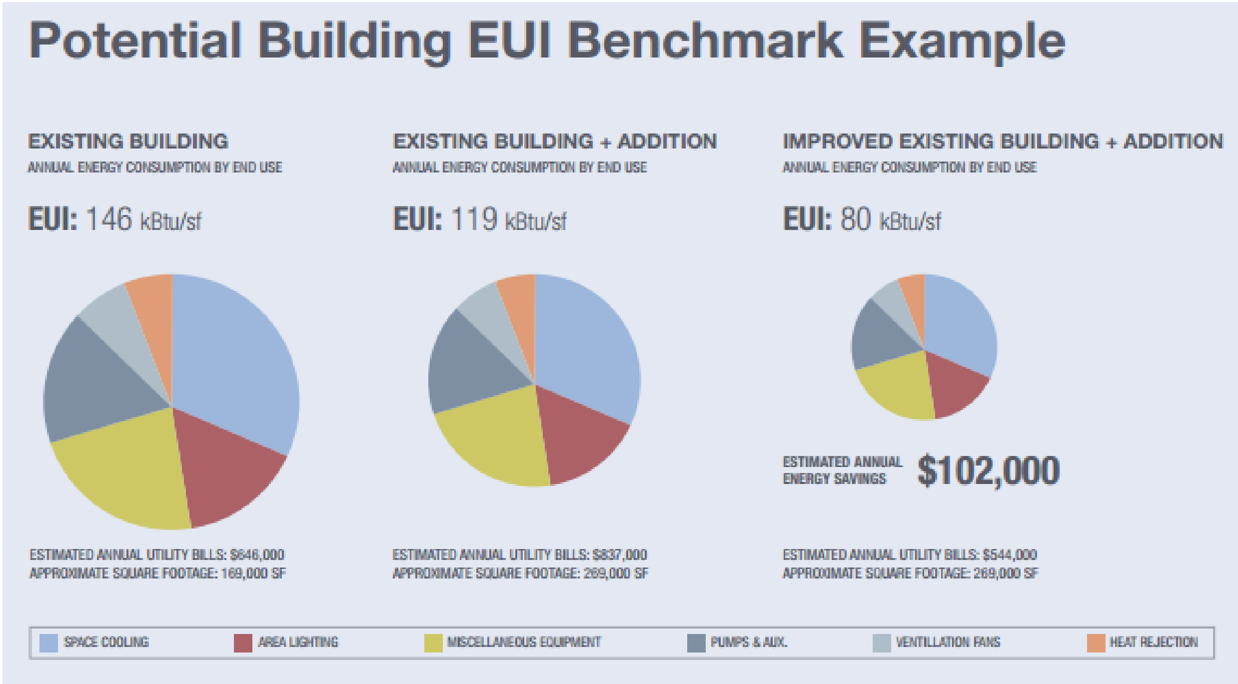

Figure 2.2. Example EUI Comparison of Potential Building Designs
extracted from (AIA, 2012)

In the information gathered from the interviewed sustainability coordinator, the energy analysis performed by his firm is used in an attempt to understand the implications of their design decisions and utilize energy analysis software to help guide a project to consume less energy. However, the process lacks a great deal of feedback and is not a precise exercise. The main criticism of such an approach is that the designs are ultimately not affected by the energy simulations, and that such methods do little to result in reduced energy consumption. These concerns are addressed later in this research.

The remainder of this section outlines the four steps outlined from the interview with the sustainability coordinator of the previously mentioned design firm.

Step 1: Existing Data and Building Survey

When a project begins, the energy analysis team tries to find EUI data of existing buildings of that particular project type in the region. This provides a very general start point of what can be expected of a typical building in terms of energy consumption.

The most common database to find this information is the Commercial Buildings Energy Consumption Survey (CBECS) which was performed in 2003 by the US Energy Information Administration. This database is the most extensive end-use survey performed for US energy consumption by building type and organized by region. CBECS is currently developing an updated survey in collaboration with stakeholder involvement with the USGBC, ASHRAE, AIA, NREL, EPA, various universities and trade associations and other organizations (Energy Information Administration, 2012). The survey is used for official government statistics, and is an excellent source of real-world data about the energy performance in the commercial sector" (Griffith, et al., 2008).

Another resource for finding existing building end-use energy consumption is the Energy Star Target Finder. Projects design to earn the ENERGY STAR certification should use the Target Finder to determine their energy performance score, but the no-cost tool can also be used generally to find data and set energy targets. Target Finder is also used per building type and region, and uses the CBECS database as a complimentary data source (Energy Star, 2012).

In addition, other organizations are currently compiling post-occupancy energy usage reports that are anticipated to be published very soon. These efforts include the University of Washington in collaboration with the Northwest Energy Efficiency Alliance (NEEA, 2012), the Commercial Building Initiative within the US Department of Energy

(DOE, 2012), the Lawrence Berkeley National Laboratory hospital benchmarking study (LBL, 2012), and the National Renewable Energy Laboratory (NREL, 2012). All of these sources will help establish baseline energy consumption for future projects based on the actual end-use data.

Step 2: Baseline Simulations

A baseline simulation is one that uses basic project data to determine what a standard project's energy consumption based on building type, location, orientation, building envelope, number of stories, and square footage. The process is that the building basic size and program square footage is determined, as well as location. Using code minimum ASHRAE 90.1 performance goals, the data is input into the energy analysis software. At this stage, the building is not yet designed and shown as a simple mass with appropriate size and shape. Sometimes a minimal amount of glazing and building envelope constraints are added to the energy model, and the simulation is run four times – once for the building oriented toward each cardinal direction.

Although the existing building survey can establish what current buildings in the region are consuming, it is helpful only as a reference point and not useful for comparison purposes. There are various reasons for this. First, there are many factors that cannot be determined strictly based on the end-use surveys. For example, the types of fuel used or the types of mechanical systems have a large impact on energy usage but are not reported in detail in most post-occupancy energy analysis surveys. Second, a building's actual energy performance is greatly based on usage, operations, and commissioning. Again, these issues are usually hard to determine for existing facilities, therefore there can be no control factor for comparison purposes.

The interviewed architecture firm using the energy analysis program eQuest, developed by the US Department of Energy, as the software for whole-building energy simulations. This organization believes that eQuest is the most accurate and simple technology for designers to evaluate their designs in terms of energy consumption. Other programs used by the firm include Ecotect and Autodesk Vasari, which provide sun shading and day lighting analysis, as well as wind tunnel analysis. These software packages are utilized mostly for their superior graphical outputs, however, and not for creating accurate energy use data.

Step 3: Proposed Design Simulations

Once a baseline energy use is established based on simple building parameters, the building enters the design phase where the building shape and location on the site is defined, the building envelope and materials are established, and the building systems are determined. Using the same eQuest software, the building data is updated to reflect the design and the simulation is run once again. By comparing the proposed design to the baseline simulations, the designers get information on how their design decision effects the building's energy consumption.

This step is the most critical and most intensely studied portion of energy modeling because it is essentially an estimate of how the actual building will perform when fully operating. This is also the energy modeling step that will be focused on over the course of this research.

Step 4: Post-Occupancy Energy Consumption Data

The architecture firm is in the process of trying to gather post-occupancy energy data of their designed buildings after construction. Post-occupancy data is information collected after the building is completed and once the building is in use. The benefit of this information is to validate design decisions and provide learning opportunities for future projects. Such information is difficult to gain access to, however, for multiple reasons. Even though many advanced organizations do use such analysis for facilities management, many institutions do not measure or record such data. The cost of procuring the data may be prohibitive, from the necessary sensors to gauge specific energy use to the software used to compile such data to the personnel required to track and make sure such systems are appropriately working. Of course, base energy use can always be gained through simple records like utility bills, however this brings up the aspect of breaching an organization's privacy.

It must be clarified that post-occupancy data is different than commissioning. Commissioning ensures that the building systems are functioning properly according to its design. While this is tangentially related to energy use, the explicit purpose of commissioning is not to reduce consumption even though that is usually the outcome from making the systems work as designed.

2.1.3. Energy Analysis Challenges

Along with the benefits of energy analysis for buildings and building systems come new challenges that must be addressed. One challenge is that simulation results are often confused with real-world data. It is a largely held belief in the construction industry that simulations should only be compared to other simulations and not be compared to actual usage (Wolfe, 2012). Comparing like simulations provide for controlled options with all other settings remaining equal. This allows for discerning ramifications of each option in a controlled environment.

Another challenge spoken about by the interviewed sustainability coordinator is that simulations also cannot be compared to actual building usage because of environmental factors. By nature, a simulation is not reflective of a real-world situation, with many assumptions and predictions occurring to make the simulation provide decent output. When simulations are compared to one another, these assumptions are the same. Yet comparing to real world phenomena will most certainly not match those assumptions. One example is the use of weather data. Simulations often utilize averages of past weather conditions as their data input. If we compare a year of that simulation model's energy use with an actual building's annual energy use, we can understand immediately that the actual yearly weather will not match the simulated data, and therefore the numbers will never be comparable no matter how accurate the simulations were. Therefore, design firms like the one interviewed never rely on the numbers extracted from energy models and only compare like simulations to each other (Wolfe, 2012).

Another large hurdle the energy simulations face is the time they take to perform. The traditional methods for obtaining and analyzing energy model analysis are a substantially lengthy process, and the results lag in time by the time they are delivered. This can make the analysis obsolete because the original answers sought in the energy model are often "irrelevant by the time they are delivered" (Bazjanac, 2008). For this reason, energy analysis on real-world projects has minimal impact on the final building designs.

The last obstacle worth noting for energy model analysis in building design is the issue of placing it within the traditional building design and construction process. The previously cited AIA guide outlines broad ideas of how an energy model can be incorporated into the various stages of building design and construction (see Table 2.1), but there is not a definitive answer as to when and how energy models are inserted into the actual process of design and construction.

Some researchers argue that this is because energy modeling does not fit into traditional building process. One study explicitly states that BEP simulation does not fit into the integrated BIM processes that the construction industry demands, nor does it match well with progressive AIA models of project delivery (Bazjanac, 2008).

That same study continues by stating that because energy modeling does not fit well into construction practices, the preparation for energy modeling usually starts too late during the design. Traditional energy modeling, the research suggests, starts only after the design is largely developed, making analysis available only *after* "fundamental design decisions, potentially critical to energy performance of the future building, have already been made" (Bazjanac, 2008).

Because of all these reasons, energy analysis is minimally used in the current construction industry. One analysis predicts that it is possible that less than 1% of typical new US buildings constructed have the involvement of some form of energy modeling.

This is because simulation is seen as too costly, too labor intensive, and too slow to deliver any real results (Bazjanac, 2008).

2.2. Introduction to Building Optimization

Over the years, "hundreds of optimization algorithms have been developed" (Zhang, 2012). In general, they belong to three broad groups: 1)gradient based methods; 2) direct nonpopulation-based search methods; and 3) population-based search methods. "Only the last group of algorithms are capable of handling multi-objective and/or multi-constraint (often called multi-criteria) problems" (Zhang, 2012). Since the current research involves multi-objective optimization, the literature review and precedent studies will focus on those methods.

2.2.1. Multi-Objective Optimization in Building Design

It is widely recognized that building and engineering construction problems are complicated. "Most engineering problems are characterized by several non-commensurable and often competing objectives to be optimized. Due to trade-offs involved, such problems usually have no unique, perfect solution" (Fonseca & Fleming, 1995). Intertwining factors such as cost, materials, schedule (time), performance, safety, and many others would like to optimized by the construction team, but there is most likely not a single solution that can optimize all factors simultaneously. Instead, there is a multi-dimensional solution set that can uncover the optimized solutions of each factor, which is called the Pareto-optimal set.

The Pareto-front is the maximal set of non-dominated elements (Cvetkociv & Parmee, 1998). A solution is considered non-dominated if the "improvement in any objective can only be achieved at the expense of degradation of other objectives, and can only be discriminated on the basis of expert knowledge of the problem" (Fonseca & Fleming, 1995). In this sense, another name for the Pareto-front is the *Trade-Off surface* (Dreo, Petrowski, Siarry, & Taillard, 2005). Figure 2.3 shows a generic Pareto-front diagramming the optimization of two fitness objectives. One example dominated solution is shown below the Pareto-curve. The Utopia Point is a non-attainable point that refers to a hypothetical solution that would maximize the fitness of both objectives simultaneously.

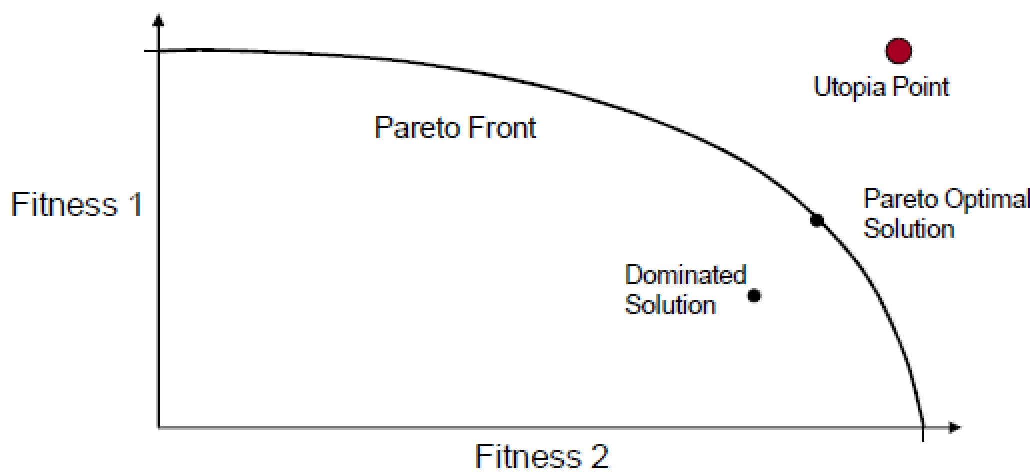

Figure 2.3. Ideal Pareto-optimal graph
extracted from (Gagne & Andersen, 2010).

The benefits of using Pareto optimization are that all objective are considered simultaneously, every element of the Pareto front is a good solution, and it maintains the diversity of solutions. The disadvantage of the Pareto method is that it is general computationally expensive, especially if the number of objectives or search space is large (Cvetkociv D. &., 1998). The traditional method of aggregating multi-objectives is to somehow combine or transform all objectives into a single-objective function. This has the opposite advantages in that it reduces the optimization to a simpler form that can be more easily computed using traditional optimization methods. However, issues arise as to how exactly to weight or normalize varying objectives, especially when the exact objectives can change over time or trade-offs want to be considered (Cvetkociv & Parmee, 1998).

One study that used Pareto optimal solutions for building design was performed in 1987 and looked at the relationship of four performance criteria used to influence the schematic design of an open plan office building. The performance factors measured were thermal load, daylight availability, planning efficiency, and capital cost. The outputs of these three study objectives are shown in Figure 2.4. The variables discussed in this study were window geometry, wall construction, roof construction, orientation, shape, floor area, and massing. The researchers conducted a case study for an office building in Perth, Australia and created Pareto-Optimal graphs where thermal load is plotted against capital cost, planning efficiency, and daylight. These simple graphs offer a powerful educational tool "in understanding the relationships between design decisions and the criteria considered" (D'Cruz & Radford, 1987).

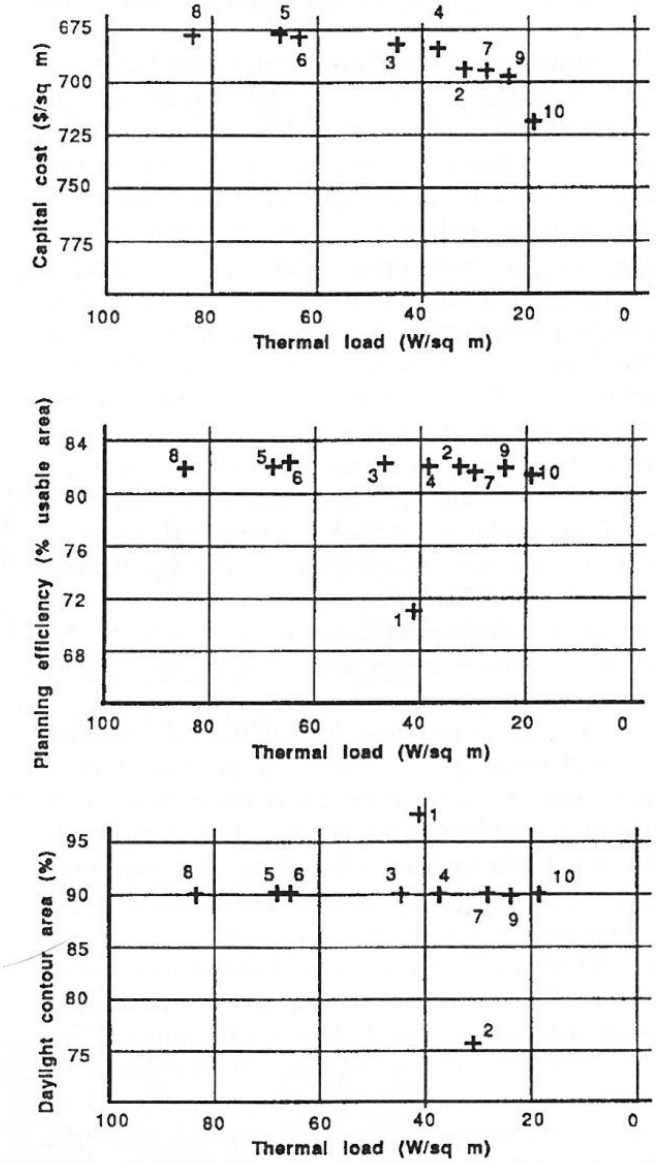

Figure 2.4. Ten Representative Pareto Performances
extracted from (D'Cruz & Radford, 1987)

More recently, researchers looked into using an iterative procedure to analyze the Pareto-front of a multi-dimensional optimization problem that was difficult to computationally derive. The goal of their research was to break down the problem into smaller-dimensional Pareto-optimal sets strictly for visualization purposes. For example, they created a graph of the bi-criterion problem of optimizing capital and operating costs for the construction of a chemical plant. While the problem was over simplified to create the graph, the visualization of the trade-off was priceless for someone looking at the implications of decreasing the capital costs of the project (Zilinksas, Fraga, & Mackute, 2006). The researchers imply that the visualization seen in Figure 2.5 is far more useful than the cryptic output of a computationally difficult multiobjective problem that has implications not fully understood by the design team. The graph is actually a reduction of a nine-dimensional case study, where lambda corresponds to the eigenvalues of the set of feasible points in the multi-dimensional search space.

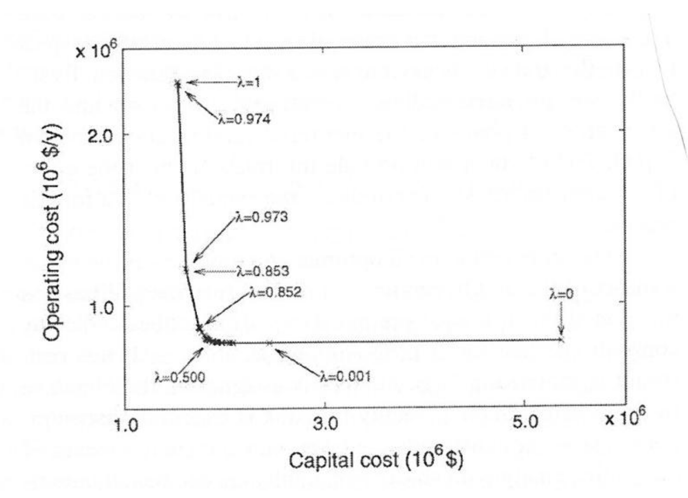

Figure 2.5. Pareto set of a Bi-criterial Problem
extracted from (Zilinksas, Fraga, & Mackute, 2006).

It is important to note the Pareto-Optimal sets are not the only method in determining multiobjective optimization for building construction. "The idea of multi-criteria decision-making methods is so natural and attractive that thousands of articles and books have been devoted to the subject" (Turskis, Zavadskas, & Peldschus, 2009). One widely used multi-criteria decision making tool is Analytic Hierarchy Process (AHP). An example of this use in combination with game theory was proposed in a 2009 study involving wall construction types in Lithuanian housing (Turskis, Zavadskas, & Peldschus, 2009). However, this research will focus on the Pareto-Front method for the purpose of narrowing the discussion topic.

2.2.2. Multi-Objective Optimization in Building Energy Simulations

Building energy analysis can be optimized through search because of the complex relationship of both linear and discrete variables that make optimization strictly through mathematics difficult. Therefore, simulations present a way for discrete and difficult continuous variable problems to transform into a single performance variable that is conceived through simulated application.

In 2006, the National Renewable Energy Laboratory (NREL) published a conference paper outlining the practical application of automated multivariate optimization tools for energy analysis (Ellis, Griffith, Long, Torcellini, & Crawley, 2006). In that paper, the authors describe that using traditional trail-and-error evaluations of building options is human-driven method that is inefficient. The process amounts to a "limited search for an optimal solution." When it comes to building simulation, the authors argue that automated optimization can evaluate large numbers of potential solutions that both refine optimized outcomes as well as minimize the possibility of converging on local maxima.

According to their research, this optimization search is also “best formulated as a multicriteria, or multiobjective, sear for a set, or Pareto-optimal front, of optimal solutions.” Such multi-objective approaches recognize that oftentimes there is more than one variable that can be optimized, and that those variables are sometimes at odds with each other. The prime example in terms of building energy optimization is the aspects of project cost and project performance, which they demonstrated graphically in Figure 2.6.

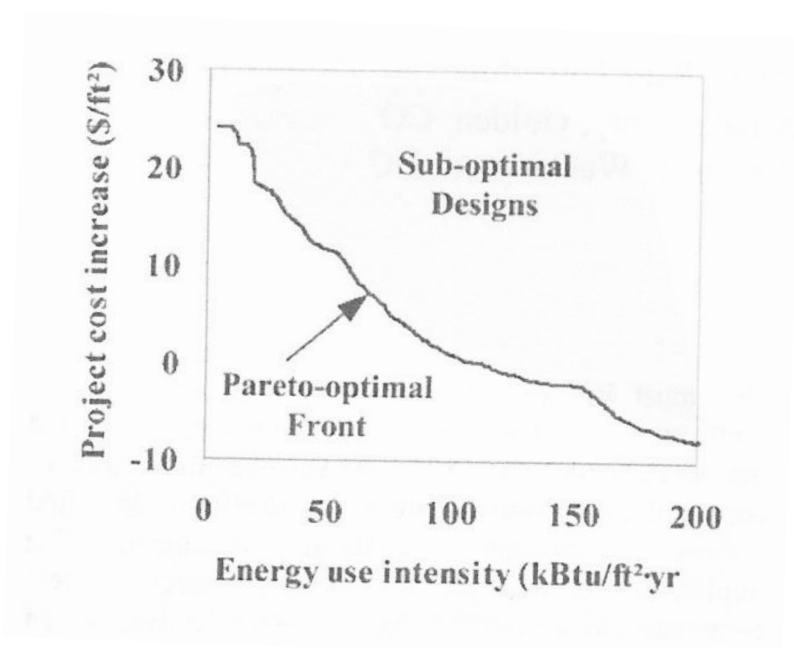

Figure 2.6. Pareto Front of Optimal Solutions
extracted from (Ellis, Griffith, Long, Torcellini, & Crawley, 2006).

It is conceivable that focusing on only one factor could limit the usefulness of any optimization exercise. For example, a certain cost optimization exercise with on objective and all other performance criteria assumed could produce a lowest cost solution. What that solution may not tell is that perhaps a minimal raise in project cost could drastically improve performance. This kind of minimum sacrifice for maximum gain may appeal to building designers or owners if they are aware. When trade-offs like these can occur, it is beneficial to present the designer with a range of optimal solutions "that can be used to inform decision-making."

Of course, the performance can be converted into a single objective or cost amount to simplify optimization. For example, a cost objective and energy use objective can be combined into a single monetary amount, but this type of consolidation would rely on a single, static price of fluctuating energy costs. Another example would be combining two objectives using a weighted proportion, based on the importance of each fitness goal as perceived by the researcher. Not only do these methods simplify the optimization process into a single objective problem at the potential danger of limiting their usefulness, but search algorithms make these additional steps unnecessary.

As the NREL (2006) paper points out, "The preferred search algorithms for finding the Pareto-Optimal front can separately and simultaneously minimize both cost and performance. This is opposed to the more common approach of attempting to aggregate and weight different metrics into a single performance index."

The National Renewable Research Laboratory researchers have access to distributed computing networks that essentially create a super-computer that can run up to 252 simultaneous simulations. Each simulation in their study could take up to two minutes, but the researchers also ran trials to determine which variables could be tweaked to greatly speed up the simulations while minimally effecting optimized outcomes. In addition, NREL researchers equipped their study with preprocessing to “autobuild” simulation input files and had access to extensive costing databases. With their equipment and technology, the NREL researchers were able to perform 545 simulations in only 2.5 hours, an average of 16.5 seconds per trial. With these instruments, it is fairly easy for the researchers to assert that “with today’s computing power, the bottleneck is no longer simulation run time, but rather the human time to handle input and output.”

The average designer, however, does not normally have access to computing power or technology of that nature. While the NREL researchers were able to run a “brute force” trial where possible solution in the search space was simulated and organized based on optimization, they also recognized the need for only analyzing selective solution sets within the search space. The question then remains as to what is the most effective way of uncovering the optimal Pareto-Front solutions while not analyzing every option. If only random solutions in the search space were tested, it would be hard to imagine the entire Pareto-Front being uncovered. Therefore, various methods were created that systematically and strategically test the search space in order to maximize the optimal solutions uncovered while minimizing the solutions being tested.

For explanation, the experiment undertaken in this research will be used as a simple example. The design problem was narrowed down to five variables with ten possible values each for this study. This equates to 100,000 possible solutions. A standard personal computer may take around 70 seconds to perform an energy simulation of that nature. If every solution was possibility was simulated using the “brute force” to find the optimal, it would take almost 82 days of pure computing time. Conversely, simulating 500 possible solutions, or ½% of the solution set, at random will take much less time but may not lead to uncovering an optimal solution. Researchers are finding strategic ways of simulating small percentages of the solution set while still finding reasonably optimal solutions.

One such area of research that attempts to address this challenge is referred to as metaheuristics. The term is appropriate as metaheuristics builds on the basic heuristic methods that concern an iterative trial-and-error processes that uncover built knowledge through discovery and aggregated learning. While there are a great many metaheuristic methods, most can be grouped into four broad categories: simulated annealing, evolutionary algorithms, tabu search methods, and ant colony algorithms (Dreo, Petrowski, Siarry, & Taillard, 2005).

The benefit of metaheuristic methods is that they can reconcile both difficult discrete optimization problems and difficult continuous optimization problems, and they can also be extended to tackle multiobjective optimization, multimodal optimization, dynamic optimization, and the recourse to parallel implementations (Dreo, Petrowski, Siarry, & Taillard, 2005). Given any solution set, one can use classical methods of optimization to incrementally improve the outcomes by through "iterative amelioration," or iterative optimization.

The risk of that method is that solutions can become trapped at local optima, and the optimized outcome is greatly affected by where the initial solution began. Figure 2.7 demonstrates a simple optimization graph that has many local minima. If a study started at point c_0 on the graph and only looked at progressively better adjacent solutions, then the output would most likely become trapped in defining c_n as an optimal solution because. At that point, every adjacent solution is less fit. However, as one looks at the entire solution set, it is obvious that better solutions exist.

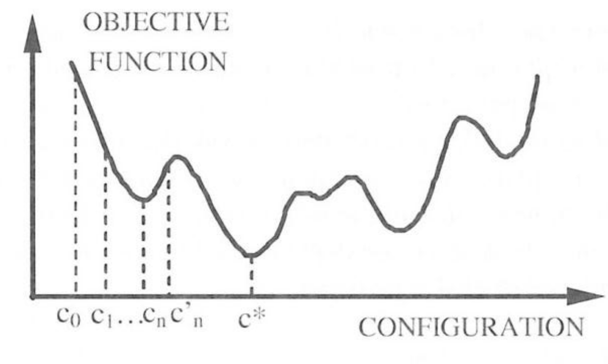

Figure 2.7. Example of Local Minimum
extracted from (Dreo, Petrowski, Siarry, & Taillard, 2005).

Metaheuristics, on the other hand, all have mechanisms to avoid becoming trapped at local minima. These methods are therefore superior to traditional optimization in that they can reliably determine the global optimum.

2.3. Introduction to Genetic Algorithms

The multi-criterion optimization method used in the proposed research is called a genetic algorithm. The reasons for choosing this methodology is articulated in more depth in Chapter 3: Methodology portion of this paper. The remainder of this section will provide a background of genetic algorithms and how they have been used in other studies.

2.3.1. Single-Objective Genetic Algorithms (GA)

One compelling metaheuristic method that has been used in construction optimization, as well as building energy simulation optimization, is called evolutionary algorithms (EA's) or genetic algorithms (GA's). As the name implies, GA's are algorithms that are loosely based on models of genetic change in a population of individuals. Initially, the algorithms define a randomly-selected population within the search space. This population is called the "solution set." Each solution has their variables defined as a string of characteristics that make up its identity. To complete the analogy, this characteristic set of "genes" is called a chromosome. The fitness of each solution is determined based on the optimization parameters, and the samples are subsequently ranked (DeJong, 1988).

As indicated by the metaphor, the solution set will "evolve" based on the fittest individuals and the process is repeated over many generations of simulation. There are a large number of variations that have been used to tweak the specific details of GA's, but three main operators are generally associated with the organized population. They are the principles of selection, crossover, and mutation.

The *selection* operator chooses the fittest instances of the population for reproduction based on the goals of the optimization. The *crossover* operator then takes the fittest solutions and mimics biological recombination by splicing and switching their chromosomes at strategic points. In essence, this is analogous to two parents distributing a portion of their genes to offspring, and the children do not always receive the same amount of characteristics from each parent.

The last operator is the *mutation* operator that randomly switches genes within a chromosome string. One main way that all optimization methods guard from converging at a local optimum is by allowing some non-optimal solutions to continue in the process. Such a strategy allows the solution set to temporarily become less optimal, with the goal of discovering global optimal solutions not necessarily near the current search set. The mutation strategy is essential the main way that GA's allow sub-optimal solutions to enter the solutions set, and they results are therefore prevented from staying at a local optimal (Mitchell, 1998).

The great appeal of mimicking natural selection is the idea of searching for optimal solutions in a huge number of possibilities (Mitchell, 1998). The terminology used to describe a large search space becoming the optimal solution set is *convergence*. Much research has focused on determining the best combination of *selection, crossover, and mutation* factors that will lead to the most beneficial convergence. Typical factors are the number of individuals in the solution set, the number of individuals to become parents, the method of crossover, the rate of mutation, and the number of generations. This balancing act of methods recognizes that an optimal solution set that converges too fast may still become trapped in a local optimal search space, but the convergence that occurs too slow may take a prohibitively long time and a large amount of computing power to reach any optimal solution set at all.

One example of a research team testing these factors in determining the accuracy of GA's occurred in 1997. At that time, the researchers found that although the results were promising, GA's could not yet compete with conventional algorithms in terms of accuracy. Using a shortest path optimization problem that looked at the minimum path distance across a varying number of nodes, they found that GA's discovered the optimal solution 100% of the time for small problems that contained only 6 nodes and 10 paths. When the problem used 32 nodes and 66 edges, the performance fell to 98%. The performance then dropped significantly when the difficulty of the problem was increased to 70 nodes and 211 edges, finding the optimal only 64% of the time (Gen, Cheng, & Wand, 1997). Of course, the accuracy was also affected by population size and frequency of the generations. Better results will be accomplished if there are more search space tests. As we will see later in this paper, great strides have been made to make genetic algorithms more accurate in selecting optimization.

2.3.2. Multi-Objective Genetic Algorithms (MOGA)

Multi-objective genetic algorithms (MOGA's) are different than single-objective GA's simply in the fact that they measure more than one fitness objective simultaneously. This provides a major divergence for how the GA works, however, since simple GA's can closely relate the fitness of the solution with its selection for reproduction and MOGA's cannot. In other words, the fittest solutions will become parents of future generations with a simple GA. With multi-objective GA, the selection of parents related to the Pareto-Front, which may include less fit solutions for any particular objective (Fonseca & Fleming, 1995).

Multi-objective genetic algorithms (MOGA's) have been improved by introducing various factors and utilizing various methods, as described in (Coello Coello, 2006). In fact, the term MOGA is sometimes associated with a specific method within the general field of Multi-Objective Evolutionary Algorithms (MOEA's), although this research paper is using it in the generic sense as a multi-objective extension of simple GA's. In addition, there have been many versions of MOEA's that are specifically developed to find the Pareto-front, such as Strength Pareto Evolutionary Algorithms generations one and two (SPEA, SPEA2). This research will not discuss the full details of each method.

Because these multi-objective evolutionary algorithms have improved over time, they are now being used in a variety of practical applications. In the field of engineering, MOEA's are being utilized in electrical engineering, hydraulic engineering, structural engineering, aeronautical engineering, robotics and control. In the field of industrial applications, where this research is focused, applications of MOEA's have been used to inform design, manufacture, scheduling, and management. Finally, MOEA's have been used in a variety of scientific applications like chemistry, physics, medicine, and computer science (Coello Coello, 2006).

One specific example of using MOEA's in engineering tested MOEA methods for groundwater monitoring applications for varying degrees of complexity. The study looked at the fidelity of using such an MOEA application by comparing algorithm solutions to reference set. One other factor they looked at was computational time. Their study found that testing 18 or less well test cases was computationally easy, however the "enumeration of the 25 test cases" took 6 days of continuous computing on their machine. The study concluded that the Pareto-optimal solutions set of each test case that were brought to a performance level of 80% created a linear scaling of Pareto set size versus problem size (Kollat & Reed, 2007). A graph of their output is shown in Figure 2.9.

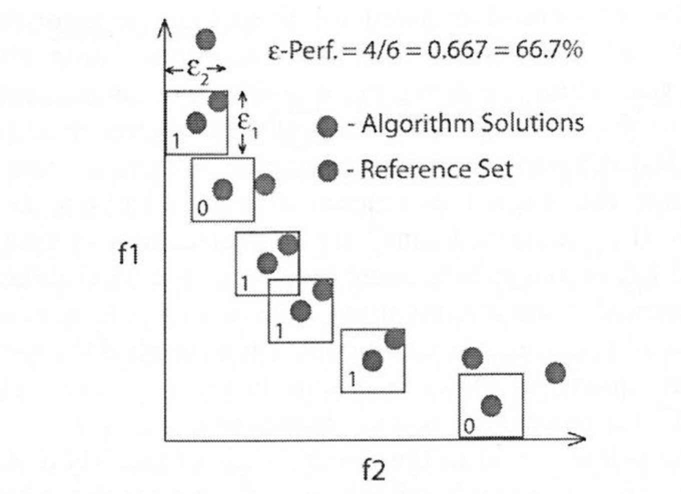

Figure 2.8. Example Calculation of the E-performance Metric
extracted from (Kollat & Reed, 2007)

2.3.3. Multi-Objective Genetic Algorithm Use in Building Energy Analysis

The research conducted in this thesis builds upon a large number of previous studies that explore building optimization through the use of GA's. There have been multiple research papers exploring the role that multi-objective genetic algorithms can play in the optimization of building performance using energy analysis and simulation techniques. Many of these research efforts also use the Pareto-optimal front as the method for determining various trade-offs between the different objective goals. The following are brief summaries of some of the research already performed on this topic.

A study done in 2002 looked at three objectives for buildings: capital expenditure, operating cost, and occupant thermal comfort (Wright, Loosemore, & Famani, 2002). Their focus was on the application of the multi-criterion decision making (MCDM) methods. The MCDM process has two elements: "1) the designer must make a *decision* as to which pay-off between the criteria results in the most desirable design solution; 2) a procedure to *search* for one or more solutions that reflect the desired pay-off between the criteria" (Wright, Loosemore, & Famani, 2002). This particular study also used the specific MOGA method as defined in other research papers. In this instance, MOGA refers to a specific form of multi-objective evolutionary algorithm that treats criteria as "goal restraints" and penalizes the Pareto rank of infeasible solutions.

The study looked at various design days for the analysis of HVAC systems: a summer design day, a winter design day, and a swing design day. The researcher trials were evaluated progressively, from one design day optimization to three design day optimization and looked at the design day energy costs versus the thermal comfort. The metric used for operating costs looked at hot water from a gas fired boiler and chilled water from an electric powered chiller. The price of electricity fluctuated based on the peak demand, and the gas price remained constant. The metric for thermal comfort was represented by the maximum predicted percentage of dissatisfied (PPD). Overall, the design day was measured in a total operating cost and maximum PPD to measure performance.

The problem's variables were restricted to looking at the HVAC system. "The size of the HVAC system is represented by the width, height, number of rows, and number of water circuits of each coil and the supply fan diameter. The maximum water flow rate to each coil is also a problem variable. The size of the heat recovery device has been fixed as has the return fan diameter. This adds a further 11 problem variables, which together with the control variables, gives a total of 200 problem variables" (Wright, Loosemore, & Famani, 2002).

The researchers concluded that the multi-criterion genetic algorithm exhibited fast progress toward the Pareto-optimal solutions. Even before a truly Pareto-optimal solution was yet discovered, the trails yielded feasible solutions within very few generations. This allows designers relatively fast feedback indicating the potential implications of their design decisions. The study predicts that multi-criterion genetic algorithm based optimizers have great potential and may "be used in the design process to enhance the understanding of the characteristic behavior of the building and design solutions" (Wright, Loosemore, & Famani, 2002). From that study, Figure 2.9 below illustrates the Pareto-front obtained by looking at the two objectives of energy cost and cost pay-off. The following Figure 2.10 shows the progression of the studies generations using the multi-objective genetic algorithm. The initial generation becomes more refined as a Pareto-front for the 21st generation, and even more optimized for the final generation.

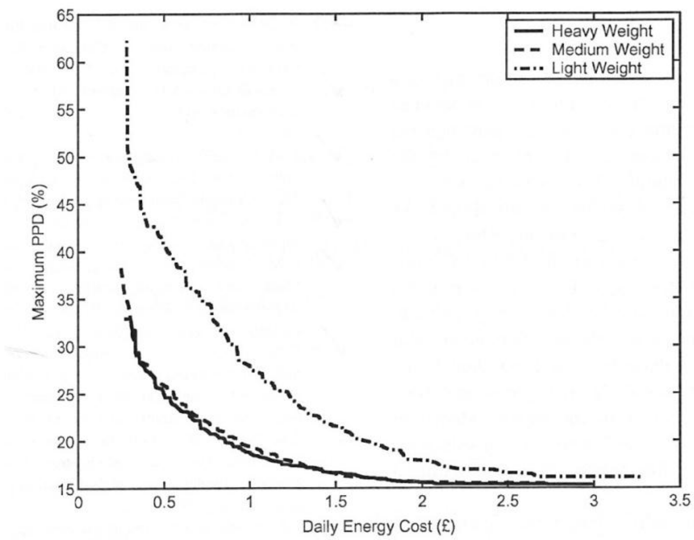

Figure 2.9. Energy Cost vs. PPD pay-off for Difference Building Weights extracted from (Wright, Loosemore, & Famani, 2002).

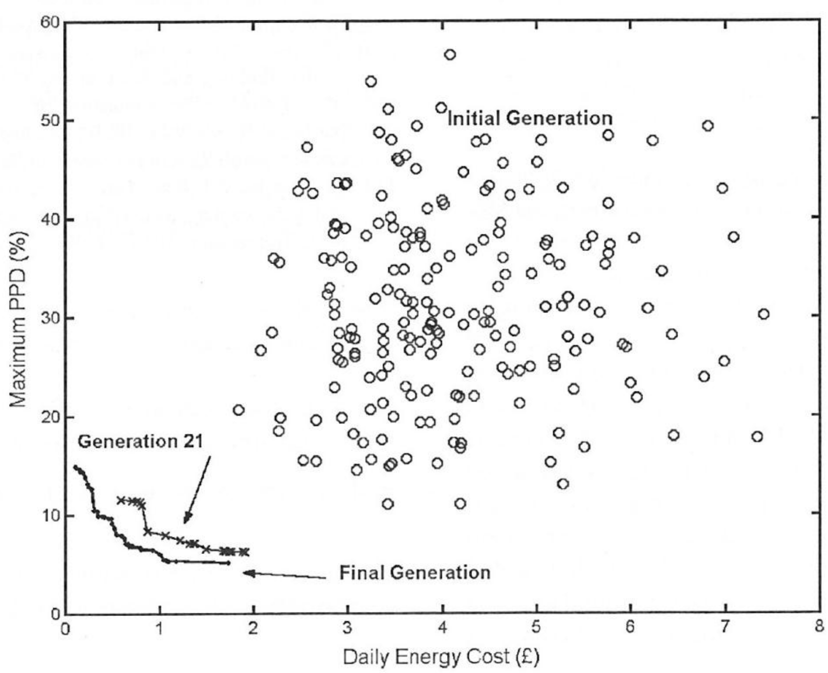

Figure 2.10. Convergence of the MOGA Search extracted from (Wright, Loosemore, & Famani, 2002).

Another research study also looked at using multi-objective genetic algorithms in determining optimal HVAC design (Caldas & Norford, 2003). This study built off previous work that looked the use of GA's in designing HVAC systems. The research included introducing a GA to schedule loading controls in lighting and cooling to optimize HVAC performance while maintaining certain constraints related to thermal comfort (PPD) as well as others.

In addition to strictly looking at the design of the HVAC system, the researchers explored the use of using GA's to optimize the building envelope. Their work was performed in three phases which looked at various optimization problems that dealt with the building envelope and used a GA to control a DOE-2 building-energy simulation program that evaluated the energy consumption of each variable through simulation.

The first phase of work by the researchers looked at the lighting and space conditioning systems by optimizing the window size and placement. The second phase of work performed by the researchers analyzed the optimization of building materials. The building materials investigated included various types of air layers, insulation materials, and concrete blocks. They ran simulations for two climates: Chicago and Phoenix. Using two climate zones provided examples of how optimization can uncover differing Pareto optimums depending on the relationship of solutions to varying types of fitness. The researchers then looked at an example trial located in a Beijing climate that studied the implications of various glazing types. The third phase that the researchers worked on "employed to alter building form to optimize the trade-off of lighting and heating energy" (Caldas & Norford, 2003). The Pareto-front of the researcher's apartment solar study is shown in Figure 2.11 below.

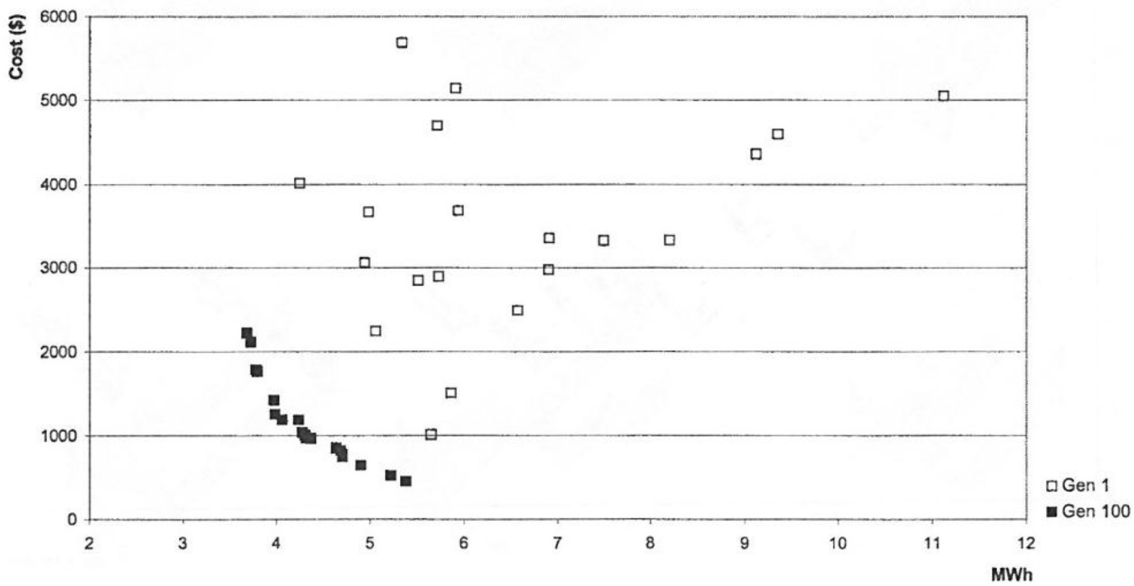

Figure 2.11. Pareto Front for Apartment Solar Study
extracted from (Caldas & Norford, 2003).

The researchers conclude the GA's have been successfully applied to many problems concerning building energy use and HVAC systems. The authors also predict that GA's will come in to more prevalent usage when energy analysis modeling program become easier to use (Caldas & Norford, 2003). Nine years later, this prediction is almost true. Ecotect (Autodesk, 2012) and Autodesk Vasari (Autodesk, 2012) are user friendly programs that utilize energy analysis software. Already the uses of evolutionary algorithms are being experimented with such platforms. In addition, the Grasshopper plug-in to shape modeling program Rhino is also becoming a graphical user-friendly coding tool (Grasshopper, 2012). This has led to Grasshopper extensions that utilize evolutionary computing like Galapagos evaluate fitness to formalize building shapes (Rutten, 2012). Such fitness objectives as energy analysis have already been used with Galapagos to determine optimal building form.

A study published in 2005 continues the research of multi-objective genetic algorithms with energy analysis, but looks at green building design much more holistically rather than simply the HVAC system (Wang, Zmeureanu, & Rivard, 2005). The paper looks again at the variables included in the initial stages of building design: orientation, building shape, window type, window-to-wall ratio, wall construction type (based on variables determining each layer of the wall sandwich), and roof construction (based on variables determining each layer of the roof sandwich). Each variable is defined as either discrete or continuous and given certain constraints.

Instead of measuring energy costs, the study attempts to look at the entire energy use of the building through Life Cycle Analysis (LCA). In order to combine energy use which is easily identifiable with less easily measureable energy use such as natural resource depletion, the research looks at the life cycle environmental impact using exergy. The definition of exergy is beyond the scope of summarizing this study. The use of exergy analysis in this case is used to combine resource depletion and waste emissions into one single objective function as well as combining fuel and nonfuel materials. The cumulative exergy consumption (CExC) used in the study combined pre-operation exergy consumption, operation exergy consumption, embodied energy of consumed fuel, mass of nonfuel material, life expectancy of the building, and other energy related factors. The LCA program ATHENA (ATHENA, 2012) was used to measure and score the LCA of each solution.

The researchers concluded the study by identifying the Pareto-optimal front of their trials. The graphical nature of mapping the Pareto-front allowed them to identify explicit trade-offs as well as easily analyze the data output. For example, groupings of Pareto-optimal solutions showed discrete regions with different optimal solutions. Also, certain variables like orientation and window ration converged to the same value for all Pareto solutions. Those specific objectives were found to have definite optimal solutions. As shown in Figure 2.12, other variables like aspect ratio and insulation materials vary within different Pareto solutions or Pareto zones (Wang, Zmeureanu, & Rivard, 2005).

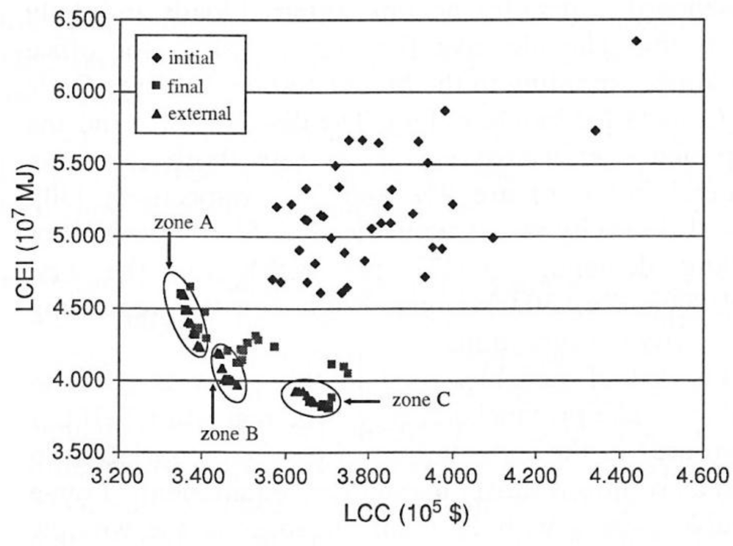

Figure 2.12. Distribution External Population in Performance Space extracted from (Wang, Zmeureanu, & Rivard, 2005).

A research study published in 2009 looked at the optimal design method for building energy systems using genetic algorithms (Ooka & Komamura, 2009). Using a modified form of multi-objective genetic algorithm called Multi-Island Genetic Algorithm (MIGA). The authors contend that MIGA is a more efficient GA because it divides each generation into sub-populations called islands, with the genetic operations are performed independently on each sub-population. Quite simply, this method creates parallel runs of each GA within each single trial of the GA, thereby increasing the rate of convergence without narrowing on a local optimum.

The researchers describe their search to achieve optimal building operations as a four-step process: 1) select basic system for the energy systems, 2) optimize the equipment capacity of each energy system (using MIGA), 3) optimize the operational process of each energy system (using MIGA), and 4) select the best design by comparing each local optimal solution. The energy demand data for this study is the default data of the CASCADE III energy simulation program released by the Society of Heating, Air-Conditioning and Sanitary Engineers of Japan, which is based on statistical data from real hospitals (Ooka & Komamura, 2009).

A final example of the use of MOGA's used in building energy optimization is a study published in 2010 that researched the design of outer windows and their effect on indoor environmental design (Suga, Kato, & Hiyama, 2010). Using energy analysis software called modeFrontier combined with MOGA code, the analysis studied the four objectives of energy consumption, cost of glass, uniformity of indoor illumination, and draft performance when windows were opened.

In this case, the uses of genetic algorithms were beneficial because all factors were discrete values: 14 discrete values for window vertical size, 16 discrete values for window horizontal size, and various discrete possibilities for window placement totaled 1680 discrete options for window size and location. In addition, 91 discrete glass types were used. For each solution set, there were four types of analysis performed: an optical analysis assessed the daylight factor and uniformity, radiation analysis was used for PMV control, heat load calculation were used for energy analysis, and CFD analysis was used to assess draft performance. Figure 2.13 shows the four-objective cluster analysis graphs extracted from the study.

In addition to looking at how the Pareto optimal solutions clustered, the research analyzed the impact of various MOGA factors. They compared the effectiveness of each MOGA run by changing the crossover rate, the mutation rate, and the population size. Each trial had a different amount of generations because the trial was designed to stop when there were no additional Pareto-optimal solutions found during any generation. The researchers concluded that "by using multivariate analysis techniques, we were able to extract knowledge from the resulting Pareto-optimal solutions set that could not be ascertained using engineering approaches, including the trade-off relationships between objective functions" (Suga, Kato, & Hiyama, 2010).

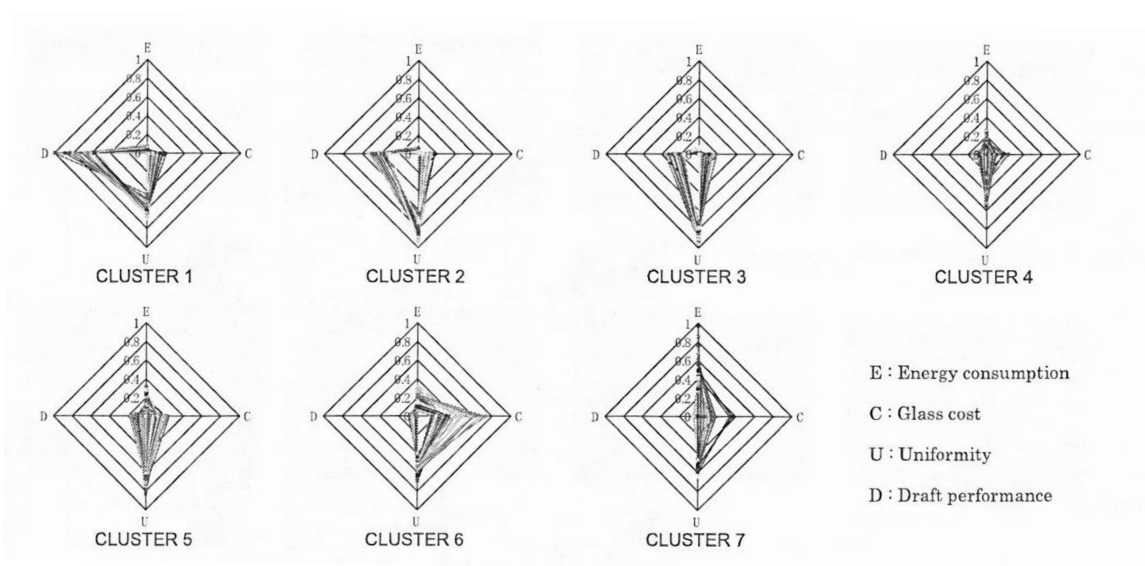

Figure 2.13. Analysis of Pareto-optimal Solution Sets Derived via Full Search extracted from (Suga, Kato, & Hiyama, 2010).

A prime reason for using GA's is due to the discrete nature of building variables. Differential equations that rely on continuous variables are not as effective in finding optimal solutions in building applications. As one NREL research paper explains the best formulation for optimization is a multi-objective search for Pareto-optimal solutions. The paper continues by saying that "for buildings, search methods need to handle discrete variables and should attempt to identify a broad portion of the Pareto-optimal front. Genetic algorithms are applicable to discrete variables" and have been studied in the building context by multiple research teams (Ellis, Griffith, Long, Torcellini, & Crawley, 2006).

In general, studies that use GA's to find non-dominated, Pareto-optimal are effective. One heavily cited study exploring building energy costs and thermal comfort successfully revealed that a multi-criteria GA is not only able to find optimal solutions, but that demonstrated "rapid evolution towards the Pareto optimal solutions. In particular, it is possible to find feasible solutions within very few trial solutions" (Wright, Loosemore, & Famani, 2002).

Additional research that compared GA's with other optimization methods concluded that the study of evolutionary algorithms has shown as a "great help of statistical models in driving the evolution of the best solution in large and complex search spaces." The researchers had combined GA's with neural network analysis to study optimized building controls and tested both single and multi-objective optimization. Their experiments found GA's to be very effective and provide "very satisfactory" results for both methods (Zemella, de March, Borrottid, & Poli, 2011). Another recent study pertaining to building control systems was equally successful. That research combined

GA's and fuzzy logic to optimize an agent-based intelligent control system for a cooling coil (Navale & Nelson, 2012).

To summarize, Tressidder et al. (Tresidder, Zhang, & Forrester, 2011) argued that for all the methods proposed to efficiently search the design space for the optimum design, "one of the most successful and extensively studied methods [are] evolutionary algorithms. These use Darwinian concepts of selection, sexual reproduction, mutation and crossover to 'evolve' better buildings from an initial sample population. This method has been shown to be effective at finding optimum designs."

The last studies mentioned above were researching energy efficient building solutions. Energy efficiency is a common optimization problem within the literature pertaining to building optimization, and many of the studies cited in this paper evaluate their experiments using that metric as well. One paper summarizes this point by citing numerous examples of past research that demonstrate how GA's are capable of finding large numbers of distinctly different low-energy designs, have been used to find environmentally optimal buildings, have been utilized successfully for analyzing building performance and LCA, and have been combined with artificial neural networks to optimize building controls (Bernardes, Benetto, Marvuglia, & Koster, 2011).

Cost optimization is also found in building optimization studies, but to a much lesser degree and usually using proxy values that allow cost optimization without strictly analyzing building construction cost. This is probably because using construction cost as a metric is difficult to defined in terms of actual costs. As the research report from NREL indicates: "Cost data are still problematic, especially for HVAC systems and equipment. Costs are also volatile" (Ellis, Griffith, Long, Torcellini, & Crawley, 2006).

In spite of their hesitation to measure costs, that same NREL report underscores the importance of cost analysis to the process of optimizing building construction. For this reason, the research presented in this paper does factor construction costs, yet with an understanding that readers should be skeptical of the actual dollar amounts presented. Although great efforts were made to obtain realistic cost data for the purposes of analysis, the cost parameters remained constant throughout the trials and results should only be analyzed as a comparative measure.

2.3.4. Practical Challenges

These research described in this literature review not only informs future study on what is possible, they also warn of certain challenges. Based on the previously reviewed background research, the main difficulties of conducting or reproducing genetic algorithm experiments of this nature are computing power, genetic algorithm convergence, and energy analysis result fidelity. This section briefly describes the nature of each of these challenges as well as this research's proposed methods of handling these issues.

Computing Power

Most of the precedent studies this paper reviewed used far more computational resources than what is accessible to the personal computer user or even commercial firm. The previously cited NREL study (Ellis, Griffith, Long, Torcellini, & Crawley, 2006) that automated EnergyPlus model simulations acknowledged this fact by asserting that "the tool currently requires considerable computing resources and is intended for in-house research to assist in DOE-funded research in support of the goal of zero-energy building."

Many of the computer systems used in these studies are beyond the reach of normal contractors, architects, and building owners who desire energy modeling to optimize their construction. For example, the web-based "best-fit" baseline study of 300,000 simulations performed by Burton & Shaxted (2012) took over fourteen days and used two computer clusters in parallel, one 96-core private cluster and one 320-core cloud based cluster. Other experiments cited in this paper used a university computer cluster to evaluate 1,036,800 design solutions (Zhang, 2012), and another took a weekend to carry out 34,560 simulations on a 256-core Linux cluster for a total execution time of roughly 27 hours (Zhang & Korolija, 2010).

Genetic Algorithm Convergence

As described previously in this section, convergence is the term used when genetic algorithms close in on an optimal solution. However, there may be many local optimums that are inferior to the global optimum within the design space. GA's that converge too fast may have found local optima rather than the global optimum. GA's that converge too slowly may never find the target of an optimal solution.

Diversity is the main key defense against converging on a local optimum. Having a large amount of diversity within the design space ensures a variety of solutions are evaluated, and that reduces the probability of a GA fixating on a local optimum. The population size, parent selection, mutation rate, and crossover method are all factors that affect convergence.

In truth, however, the methods used in GA analysis are stochastic, and no amount of study can guard against premature convergence. “Premature convergence is a common problem with EAs. One of the strategies to tackle this is to perform several independent optimisation runs in parallel, therefore increase the chance of finding the global optimum” (Zhang, 2012).

This random nature of genetic algorithms means that any two trials, even ones using identical methods, can potentially provide very different results. Previous optimization research using genetic algorithms often use multiple trials to validate results. (Zhang, 2012). Although a large amount of simulation runs proved too computationally exhaustive for the equipment used in this research, attempts are made to reproduce some trials more than once in order to provide more robust results.

Energy Analysis Result Fidelity

Energy models are virtual simulations and will never be completely accurate predictors of future building performance. It is important, however, that the energy simulations are seen as realistic interpretations of what can happen over the course of a building’s lifespan. Some researchers are skeptical. One study summarized the findings of a body of research and concluded: “traditional energy performance simulation and analysis is in general based on potentially arbitrary model definitions.” That same study also claims that energy analysis “quantitative results are not reproducible and can be trusted only under special circumstances: It typically results in over–prediction of energy savings in buildings” (Bazjanac, 2008).

Another researcher describes the shortcoming of energy analysis in this way: “Most commercial buildings do not perform as well in practice as intended by the design and their performances often deteriorate over time" (Pang, et al., 2011). Two previously cited research studies tackled this premise by comparing EnergyPlus simulation results with real-world data compilation. In general terms, these two studies found that although the overall correlation was acceptable, there were some drawbacks to making direct comparisons between the virtual and real worlds.

The study of EnergyPlus simulations synchronized with real-time building data sensors articulated the difficulties of exactly matching the two formats (Pang, et al., 2011). One issue was matching weather data with the energy simulations. Generally, simulations use historical weather data based on geographic location, but real-time special weather files needed to be created to exactly match real-time analysis. Also, computation time is an issue. By default, the EnergyPlus time step is 15 minutes, meaning that output results are compiled in simulated 15 minute increments. While this level of coarseness is appropriate for general results, it was insufficient for complete comparison. The authors suggested the use of one-minute time steps for future research, but that would increase the computational resources required by a factor of fifteen.

The other drawback to comparing simulated results to real-world data is that humans are not as predictable as a model. Much of the discrepancy found in the research compiled by Pang et al. (2011) could be accounted for by human interactions that strayed from the programmed usage. For example, one night of energy simulation predication was wildly incorrect in the energy use that actually occurred. It turns out that this incongruity was the result of someone leaving the lights on overnight, an action not predicted by the computer model.

The other study conducted by NREL (Griffith, et al., 2008) compared EnergyPlus simulation results to data compiled by 2003 CBECS real-world survey data. As previously mentioned, most of the commercial sectors were in overall agreement with the energy models. According to the report, the "modeling tends to track the survey results fairly well across difference subsectors, except for education, food service, inpatient health, and public order and safety" (Griffith, et al., 2008). A graph over their findings comparing EnergyPlus model output with 2003 CBECS survey data can be seen in Figure 2.14 below.

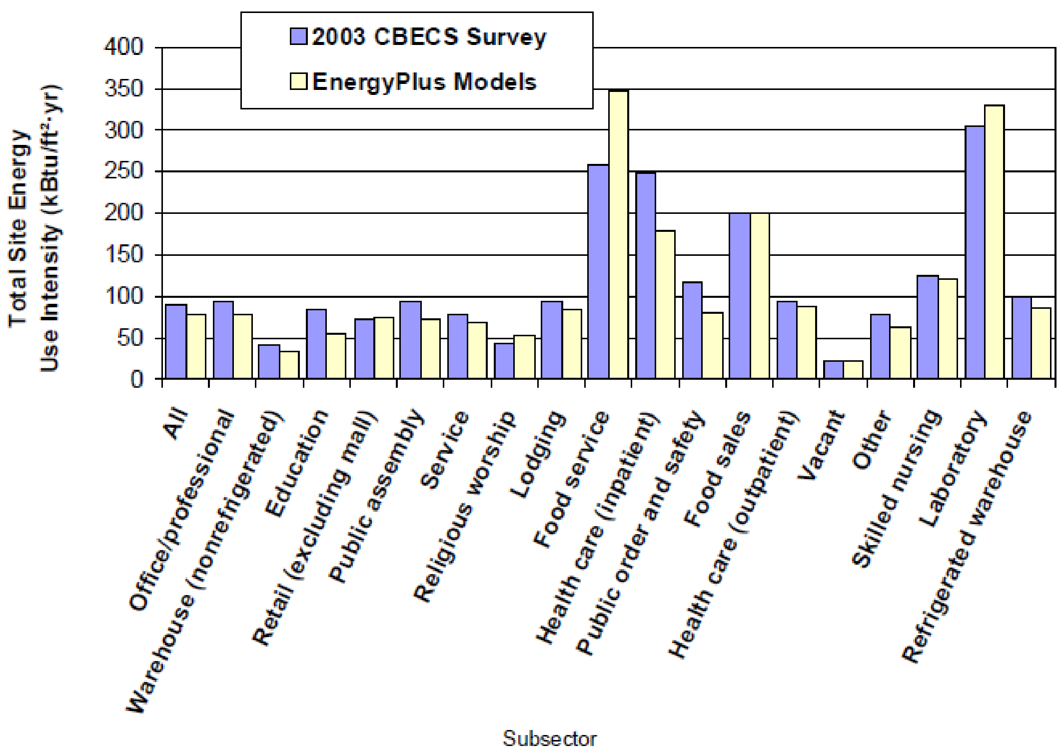

Figure 2.14. Total EUI: 2003 CBECS Survey and Modeling by Subsector
taken from (Griffith, et al., 2008)

Unfortunately, the current research is investigated energy usage of an inpatient healthcare facility, one of the subsectors that do not align in the above findings. This thesis still focuses on healthcare facilities because of their energy intensive use and the fact that they are critical building types. Reducing energy consumption in healthcare buildings in any capacity will greatly reduce building energy use overall.

Yet that is not as relevant to the current study because the simulation data extracted are not intended for real-world use. The data from this experiment is intended to find optimal design solutions based on similar virtual simulations. Therefore, each result is relied upon solely for comparative reasons. While it is ideal to have realistic outputs to insinuate real-world implications, that is not the objective of this research. The current research will not encounter the issues of incongruous weather data, human interaction diversions, or real-world implications because it does not propose using the results in a real-world application.

2.4. Research Precedents

While many previous research studies have relevance to the topics introduced in this current thesis, the details of research methodology used in this thesis were modeled after a limited number of specific research precedents. These precedents are described in this section, along with the reason they were chosen as examples to be expanded upon. Some precedents are examples of proven methods of performing genetic algorithms; some are examples of experiments expanding on those proven methods of performing genetic algorithms; and the last form of precedent evokes the idea of indexing energy simulation results for the purposes of future building design decision.

The objective of this research is to test a method that makes the genetic algorithm optimization process generally more efficient for problems concerning building design and construction. Previous studies have had the same goal and looked at addressing the practical challenges outlined in the previous section. The following is an overview of some precedent research that inspired this thesis.

Table 2.2. Table of Precedent Research and Benefits

Precedent Research	**Optimization Benefit**
1. Genetic Algorithm Parameters for Efficient Convergence	The ability to find a global optimal solution with the least amount of time and resources.
2. Automated BIM Energy Analysis	Reduce energy model set-up time.
3. Real-time Energy Simulation	Reduce energy model optimization time and minimize delayed results.
4. Simulation Indexing and “Best Fit” Comparisons	Reduce optimization initialization time.
5. Initial Population Seeding	Reduce optimization performance time.

Table 2.2 above lists the categories of optimization efficiency that were evaluated and researched. Next to each category is a brief description of how each method tries to make the optimization process more efficient.

For the general premise of efficient optimization, the current research advocates all the methods described in Table 2.2 which can conceivably be used in agreement and conjunction. For the purposes of experiment, however, this thesis will narrow its focus solely on reducing optimization initialization time, which is articulated in items 4 and 5 above.

Item 4 advocates indexing a large database of simulation results. These results, while admittedly not completely appropriate to every design problem, can be used on a "best fit" basis to begin the process of a new optimization exercise. The premise is that a "best fit" baseline is already partially optimized and can reduce the amount of initial set up time required when compared to starting an optimization exercise from scratch. Item 5 reduces total optimization time by performing a partial-optimization sub-routine before the actual optimization trial.

This research modifies the traditional genetic algorithm method with a process that combines the precedent studies from items 4 and 5 in Table 2.2. The point of departure of this thesis is in proposing the use of a "best fit" solution from a simulation index to actually be the partially optimized initial population. In this way, the simulation index is the initial population seeding for future simulations.

The following sections describe all of the five precedent methods listed in Table 2.2 above in more detail.

2.4.1. Genetic Algorithm Parameters for Efficient Convergence

The method of performing genetic algorithms used in this thesis was largely based upon the work of Wang et al. (2005) who used a multi-objective genetic algorithm to optimize a hypothetical green building. This work was chosen as a model because it was a clear and concise approach that built upon established research. The study used optimization goals of minimizing energy use and LCC to create an optimal building design. The variable parameters used for their experiment included building orientation, glazing type, and percent glazing among other variables.

The GA employed in both the Wang et al. (2005) study and this thesis utilizes the framework proposed by Fonseca and Fleming (1998), with some exceptions. The Wang et al. (2005) study expands on this GA and utilizes an improved "structured GA." Their research performs a tournament ranking method and performance improvement techniques of mating restriction and elitist strategies. In Fonseca and Fleming's (1998) work, the rank of an individual is equal to "one plus the number of solutions in the current population that dominate it" (Wang, Zmeureanu, & Rivard, 2005). Each solution in the population is given a rank based on that assessment.

The entire population is then sorted based on rank, and a normalized fitness value is established for each solution based on the sum of the entire population. This process is set up so that the lowest Pareto-ranked individual received the maximum normalized fitness value. This method establishes fitness proportionate selection for mating, which chooses parents based on probability. The selection is random, but the solutions with the highest fitness value have the most probability of being selected. That probability is determined by the proportion of their fitness value to the compiled fitness value of the entire population. The benefit of such a method is the premise that less fit solutions may have some positive characteristics and they are given a chance to reproduce while still favoring the fitter individuals during selection.

The work of Suga et al. (2010) studied which genetic algorithms produced the best results, in that which provided reasonable convergence on an optimized solution with the least amount of computation. That research attempted to optimize building's window design based on multi-objective criteria that had four separate goals: minimize energy consumption, minimize cost, maximize window uniformity, and maximize window draft performance. The study analyzed seven different trials of GA using that same research problem and compared the results. Each trial outputted slightly different Pareto-optimal sets, which allowed them to make conclusions regarding the optimal GA parameters of population size and mutation rate.

Suga et al. (2010) found that minimizing the population size drastically reduced computation time (also called calculation cost). Reducing the population too much, however, has the potential to reduce the accuracy of achieving a truly optimal solution set. Their research found that "reducing the population size to 100 had no impact on solution accuracy, while a reduction to a size of 50 was observed to reduce solution accuracy drastically."

Another GA parameter established by Suga et al. (2010) was the mutation rate. They found that establishing a mutation rate too high or too low leads the Pareto-optimal set to converge rather slowly. In addition, those mutation rates deemed too high or low affected the overall accuracy of the resulting solution set. They assessed that "a mutation rate of 0.05 is optimal."

The goal of this thesis is to not merely replicate a GA model, but to compare an augmented GA trial against the traditional model. This aspect of research was generally established by another precedent study of low-energy building optimization (Tresidder, Zhang, & Forrester, 2011). This study attempts to find the Pareto-optimal solutions of the same design problem twice: once using traditional stand-alone GA methods, and once using an augmented that method with additional optimization sub-routines. This method of interim optimization was called "surrogate modeling" in their research. However, the cost of using the optimization sub-routine versus its benefits was not clearly defined.

The Tresidder et al. (2011) paper also was chosen as a model study due to its content: building efficiency was the general objective, window glazing percentage was used as one of the parameter variables, and jEPlus was the computational tool. Notable features of the research that do not apply to the current topic are: the use of a single objective fitness function rather than a multi-objective one, differing specific GA parameters, and optimal analysis based on an earlier "brute force" simulation effort. The last point indicates that all possible solutions in the design space were simulated so that the true optimal solutions could be known. While this is a beneficial method in knowing how close any particular GA generated Pareto-optimal set is to the global optimum, the computational resources required to perform this analysis was beyond the scope of this research.

2.4.2. Automated BIM Energy Analysis

Building Information Modeling (BIM) has created an easier way to create energy analysis models. Because BIM models are embedded with information like material and cost data, this data can easily be extracted in order to analyze the design. In addition, the use of three dimensional modeling in BIM models allows energy analysis models to be created more easily and be streamlined into the process.

BIM is starting to become commonplace in the Architecture, Engineering, and Construction (AEC) industry, although still in its early phases. The technology is quickly being adopted by more firms because an integrated model leads to a more streamlined project. Still, it is not ubiquitous in the architecture world. Only 16% of AIA member-owned architecture firms had BIM software in 2006 (Zeiger, 2008). Although that percentage is small, the number of firms utilizing BIM software will inevitably grow. For example, a 2010 survey of project starts by Texas Construction magazine found 29 out of 55 projects used BIM in some capacity (Buckley, 2010).

One of the main benefits and issues of BIM purported by experts is that decision made in the early design phases "have a major influence on the overall project costs" (Baldwin, Austin, Hassan, & Thorpe, 1999). This can be a benefit if the BIM model guides decisions based on optimization of project objectives, but it can also be a problem if the information is mismanaged in the beginning project stages. The latter scenario can ultimately result in costly problems due to improper design decision made too early in the project without the proper analysis.

BIM has the potential to be a powerful took in analyzing optimal design considerations. Energy models and cost models can be used directly from BIM models, making it efficient to analyze multi-objective problems with very little additional effort. As one researcher stated, “Building Information Modeling (BIM is emerging as an innovative way to manage projects. Building performance and predictability of outcomes are greatly improved by adopting BIM. As the use of BIM accelerates, collaboration within project teams should increase, which will lead to improved profitability, reduced costs, better time management and improved customer/ client relationships” (Azhar, Hein, & Sketo, 2008).

The use of BIM models also allows the entire AEC design process to be reconsidered. Traditional building design is comprised of limited design options with minimal iterations and most time dedicated to management. One research paper proposes that the inclusion of BIM in the process makes the building design process more amenable to design processes used in other industries like those used in the aerospace industry (Flager & Haymaker, 2009). These more technical industries like aerospace engineering focus on simulation to create many design options for optimization, and use less time managing the outputs. As the researchers conclude, “Decisions made early in the design process have a significant impact on the life-cycle economic and environmental performance of buildings. Engineering simulation supported by product models is becoming state-of-the-art practice in the AEC industry. However, the potential of this technology to inform early-stage design decisions has not been fully realized because current tools and processes do not support the rapid generation and evaluation of design alternatives” (Flager & Haymaker, 2009).

Yet extracting energy modeling information from a BIM application is by no means automatic. One process being developed uses the internationally recognized IFC file format to map BIM components to elements used for conceptual phase energy analysis (Building SMART Norway, 2009). In that process, BIM input data includes: building geometry, the layout and configuration of spaces, building orientation, building usage, internal loads and schedule for lighting, occupants, equipment, HVAC systems, space conditioning requirements, utility rates, and weather data.

The energy analysis output may include: assessment of the space and building energy performance for the compliance with regulations and targets, overall estimate of the energy use by space and for the building and an overall estimate of the energy cost, time based simulation of the energy use of the building and time based estimate of utility costs, lifecycle estimate of the uses and cost for the building (Building SMART Norway, 2009).

Once BIM is converted into a usable energy model format, it must be coupled with a building simulation program, which in turn can be coupled with an optimization system to investigate optimal energy efficiency. This process involves three basic steps: 1) prepare the simulation job of the specific energy model; 2) run the simulation program; and 3) collect the results for comparison and analysis (Zhang, 2012).

2.4.3. Real-time Energy Simulation

A study comparing EnergyPlus results to real-world data took a different approach to the traditional energy modeling which segregates the energy model from real-world data. The Building Controls Virtual Test Bed developed by Lawrence Berkeley National

Laboratory does not simply compare virtual trials with a real-world database, it provides a platform to synchronize and exchange data with EnergyPlus simulations in real-time.

The researcher's reasoning is that conventionally, EnergyPlus is used for off-line analysis of building design and HVAC sizing. "With the increasing need to improve building performance, the use of simulation to assess the actual performance of buildings is starting to gain more attention" (Pang, et al., 2011). Like the previous study, the comparison of virtual and real-world results worked well together in terms of total electric power consumption overall. Even so, there were specific drawbacks uncovered in the study, many of which were discussed as practical challenges of optimization in the previous section.

2.4.4. Solution Indexing and "Best Fit" Comparisons

The penultimate topic of specific precedent research has to do with indexing solution sets. This current research had a number of precedent studies to draw upon regarding indexing energy simulation results in order to quickly and easily identify possible solutions for future designs.

The overall notion is that by indexing simulation results, future studies and real-world building design applications would at least have comparable reference points during their initial phases. Otherwise, each project is essentially starting from scratch. Zhang (2012) addressed this issue when he noted: "One of the main reasons is that optimisation problems involved in building design and operation vary vastly in nature, whereas there is not a 'generic' algorithm that is suitable for all problem types. To solve a problem effectively, researchers have to master the optimisation techniques, often by the means of implementing their own algorithms."

One study conducted by NREL (Ellis, Griffith, Long, Torcellini, & Crawley, 2006) is developing tools to automate the process of creating and running EnergyPlus simulation models across a wide array of parameters. The research uses a broad search engine that defines the EnergyPlus models and then indexes all input data and results files.

Another research study found in the literature makes the database accessible on the web in order to give building creators and users an easy-to-use tool that provides a starting point to building design that inserts energy modeling in the forefront of the design. The tool "matches a 'best-fit' baseline energy model drawing from industry publications specific to a particular building type and allows building owners to determine appropriate energy conservation measures." The tool then filters the models based on best energy performance. Finally, the database of energy models and conservation measures "are then paired with matching incentives and industry partners who can design, fund or implement the recommendations, focusing specific and pointed advice at building owners" (Burton & Shaxted, 2012). The study ultimately used jEPlus to index over 300,000 energy simulations for a variety of "best-fit" baseline energy models.

2.4.5. Initial Population Seeding

The concept proposed in this thesis of beginning a GA with a non-random and partially optimized population also has precedent in previous research. A study by Hamdy, Hasan, & Siren (2011) had the aim of achieving low-emission and cost-effective design solutions and suggests "seeding" the initial GA population with non-random solutions. They argue that "since GA starts searching by randomly sampling within an optimization solution space and then uses stochastic operators to direct a process based on objective function values, a large number of generation are usually required to achieve an acceptable Pareto front." They also claim that a high quality of Pareto-optimal solutions cannot be guaranteed by using random sampling and a specified number of GA generations.

The Hamdy et al. (2011) research differs from the current study in that they proposed using a three phase system: 1) a preparation phase, 2) a GA phase, and 3) a refine phase. The current study proposes consecutive GA phases be used to generate initial population. In addition, whereas the precedent research has a refine phase that considers realistic stopping criteria, the current experiment simply stops after five generations. There are many other differences, but the last notable one is that the Hamdy study also uses a "brute force" technique to evaluate its findings.

CHAPTER 3: METHODOLOGY

The goal of this thesis is to investigate an augmented genetic algorithm method that provides a general cost savings with reasonable accuracy. With respect to building optimization, the aim was to produce an effective solution within a timeframe that provides useful information at the right time during the design and construction process. To do test the proposed approach, the augmented genetic algorithm was compared to a traditional genetic algorithm. Refer to Figure 3.1 for a diagram of the four general steps used in this study.

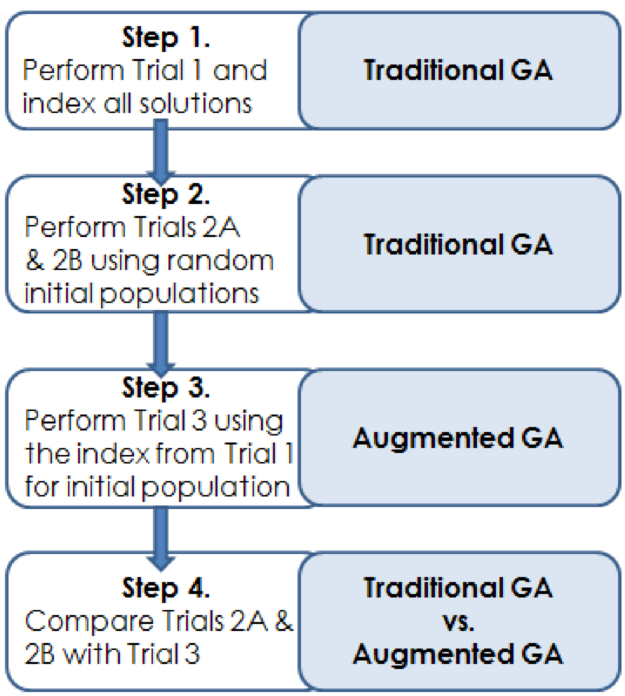

Figure 3.1. Diagram of Research Method

This chapter outlines the methodology utilized in this research and is divided into three sections. The first part provides descriptions of the steps taken to perform the experiment. This section also illustrates how the last trial run initial set up is different from its predecessors. The second part summarizes the parameters and framework set up to fulfill the proposed experiment. The final section describes the research's potential implications as well as its limitations.

3.1. Research Methods

This section describes the methods of optimization and indexing used in this thesis experiment. The first method is using a traditional GA that was extrapolated from the research precedents. The second method uses an augmented GA approach that uses a cumulative index to initialize the optimization exercise. The process of indexing solutions is also described in this section.

In general terms, Figure 3.2 compares the two GA method decision trees. One can see that every step is identical in each trial with the exception of the creation of initial population. The following section describes each step in greater detail.

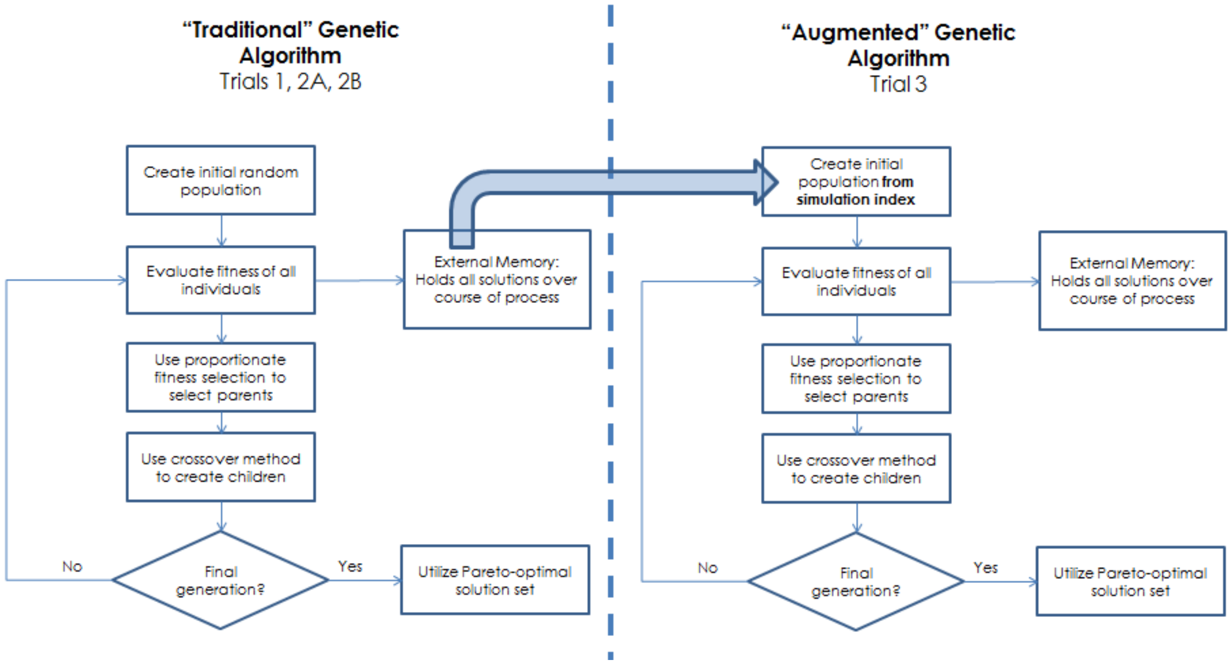

Figure 3.2. Comparison of Optimization Methods Used in the Research

3.1.1. Research Set Up

This section outlines the basic research set up performed to initialize the experiment, and further information about the exact properties and tools used during the set up are outlined in great detail later in this section. The experiment was initialized with the creation of the energy model. The energy model was created in part using the EnergyPlus simulation add-on programs EP-Launch and IDF Editor.

As a concept for possible applicability, the current research wanted to be accessible to all computers. Therefore, the approach taken was to perform all simulations on a standard personal computer with four-core processing capabilities and a 2.4 GHz processor running Windows 7, 64 bit. All screenshots provided in this section are taken from the researcher's personal computer to illustrate the steps of research that was performed.

Figure 3.3 shows a screenshot of the EP-Launch program. The input IDF file shown is the actual energy model data file, and the weather file for Atlanta, Georgia is also shown being utilized. The series of buttons on the lower portion of the dialogue box indicate the many output formats that are potentially created through the energy simulation.

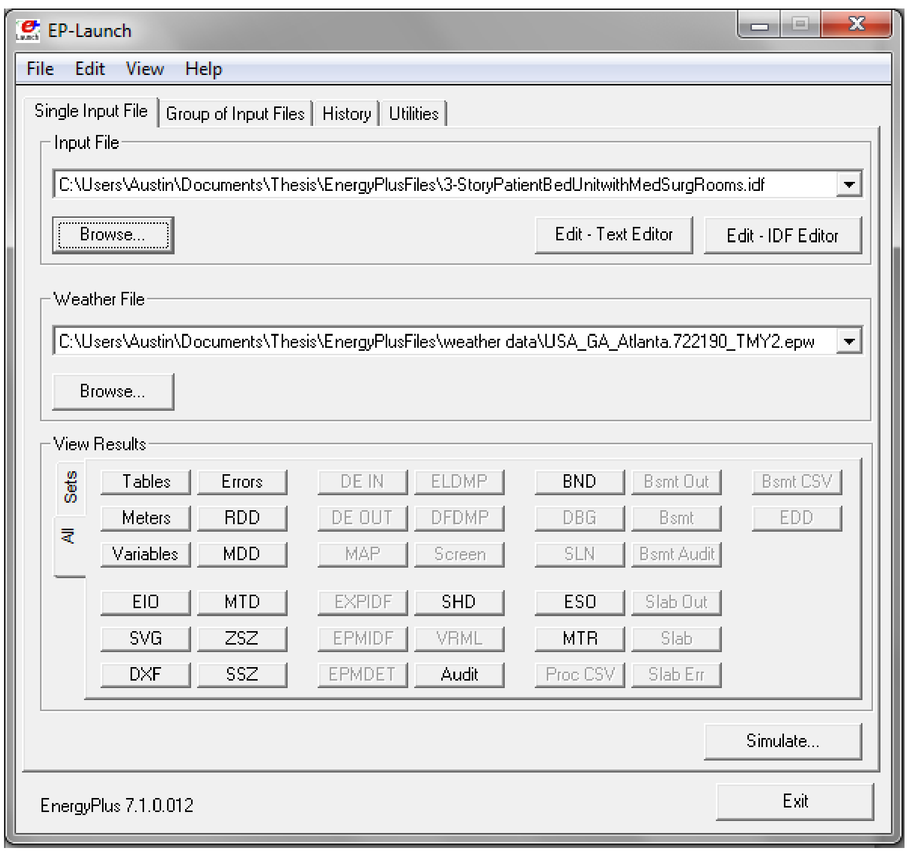

Figure 3.3. Screenshot of EP-Launch Used for the Energy Model

Figure 3.4 shows the actual energy model file used for the simulations using the IDF Editor program. All data pertaining to the energy model can be created or edited using this dialog. For example, the screenshot provided highlights the materials and material properties found in the energy model. Those materials are then compiled into construction assemblies, which are subsequently assigned to building geometries.

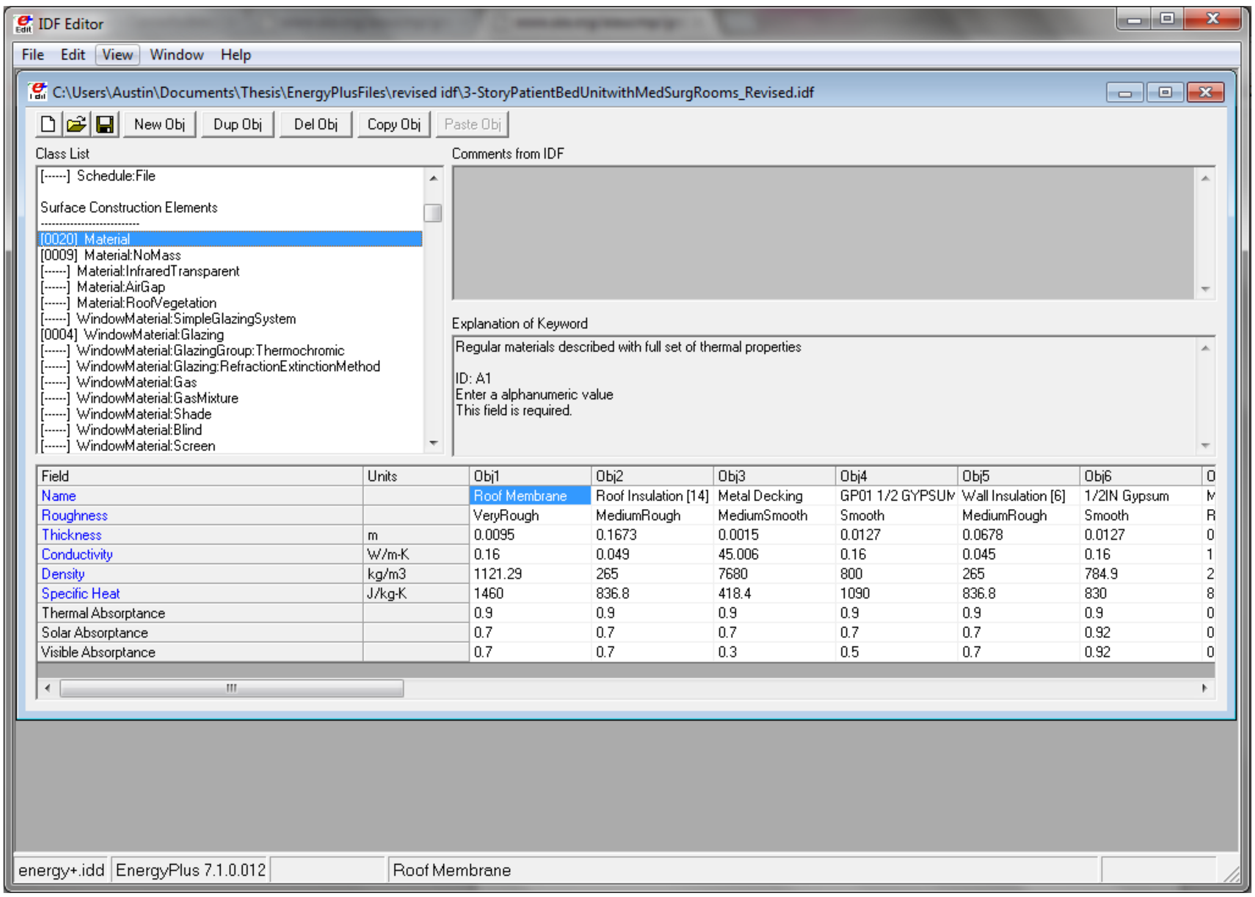

Figure 3.4. Screenshot of IDF Editor Used for the Energy Model

3.1.2. Optimization Methods

Two types of trials were preformed: 1) Traditional Genetic Algorithm, and 2) Augmented Genetic Algorithm. The first trial (Trial 1) used the traditional method and established the study as well as the simulation index. The second and third trials (Trials 2A & 2B) also used the traditional method and were used as controls. The final trial (Trial 3) used the augmented method and was subsequently compared with Trials 2A & 2B for general effectiveness.

Traditional Genetic Algorithm Process

The traditional GA is performed in a series of five steps, outlined below:

Step 1. Create an initial population of 100 solutions. For each solution, the values of each variable are chosen at random. Therefore, each solution is itself a random selection with the search space.

Step 2. Each solution is evaluated in terms of fitness. Every solution is simulated in EnergyPlus using the batch jEPlus interface. Construction cost and energy use data is automatically calculated by the energy simulation. The results from every solution are compiled and given a Pareto rank based on dominance and then sorted by rank.

Step 3. The solutions are selected based on their proportional fitness as compared to the entire population. The better the fitness, the more likely a solution is to be chosen. In this way, the fittest solutions will be selected more often but less fit options still have the potential to be selected. Less fit solutions may have optimal traits even though their overall fitness is not optimal. These selected solutions will become the parents of the next generation of one hundred solutions. Therefore, two hundred selections occur (two parents for each child). Solutions are weighted proportionally but selected at random. A single solution can be selected multiple times.

Step 4. The next generation of one hundred solutions is created. These solutions are often called children during this stage, since they are the product of two parent solutions. We will define each parent as either Parent 1 or Parent 2. Child creation is done in two phases: crossover and mutation. With only five variable traits, a single-point crossover was used. The crossover location was chosen at random. The variable traits of Parent 1 are passed to the child up to the crossover point, and the variable traits of Parent 2 are passed to the child after the crossover point. Mutation of each trait was given a 5% chance of mutating to a random value. There was no mechanism to prohibit a mutation that results in the same trait.

Step 5. The children become the solution population for the next generation, and the process restarts at Step 2. If it is the final generation, the children become the last solution population. A set number of five generations were used for this study.

Trials 1, 2A, and 2B were all performed using the five steps above. To avoid premature or local convergence as a baseline control, Trial 2 in the current experiment was conducted twice (Trials 2A and 2B). Because this trial acted as the control for the experiment, it was important to make sure that the results were as valid as possible. For this reason, Trial 2 was done twice. This provided analysis that would demonstrate whether the controls were consistent and reliable, and also created multiple controls for the experimental trial with which to compare. Trial 3 used an augmented process as described in the next section.

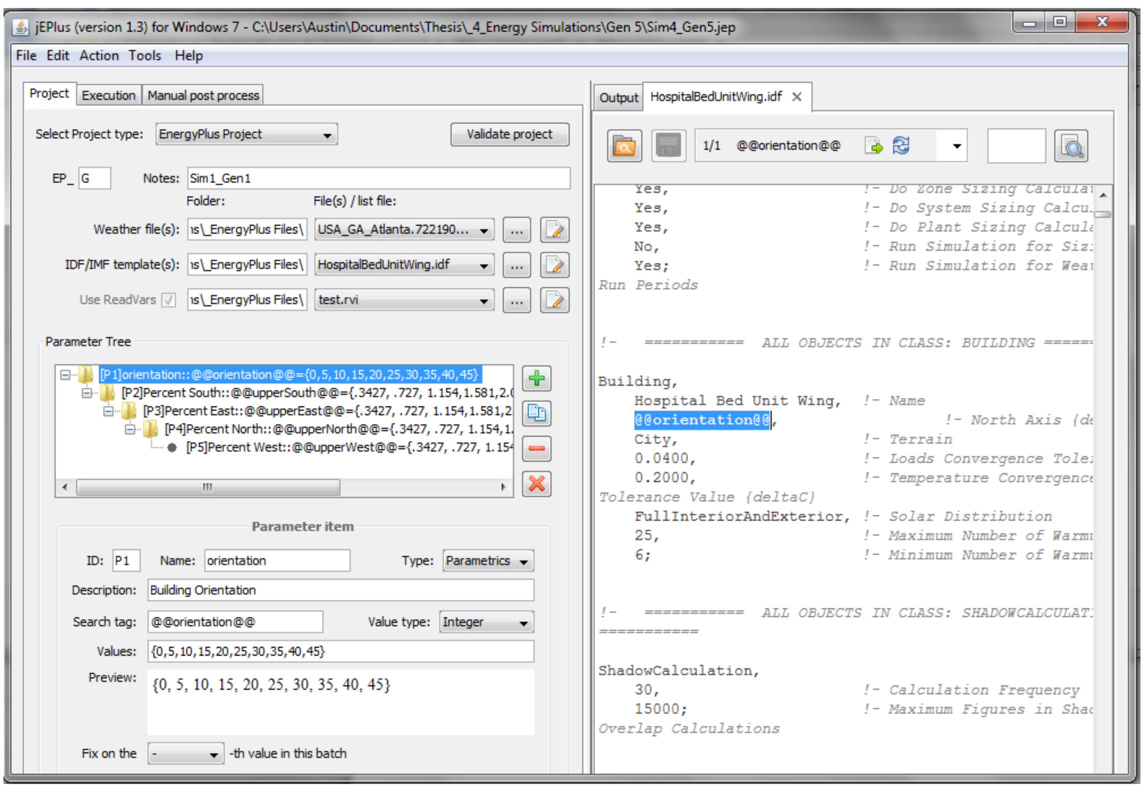

Figure 3.5. Screenshot of jEPlus

jEPlus is the program used for Step 2 of performing batch simulations that ultimately determine a solution's fitness. Figure 3.5 above shows a screenshot of that program. The dialog box shows the input EnergyPlus and weather files utilized, the specified parameters used for batch processing, and a preview window that allows manipulation of the input files to insert parameter placeholders.

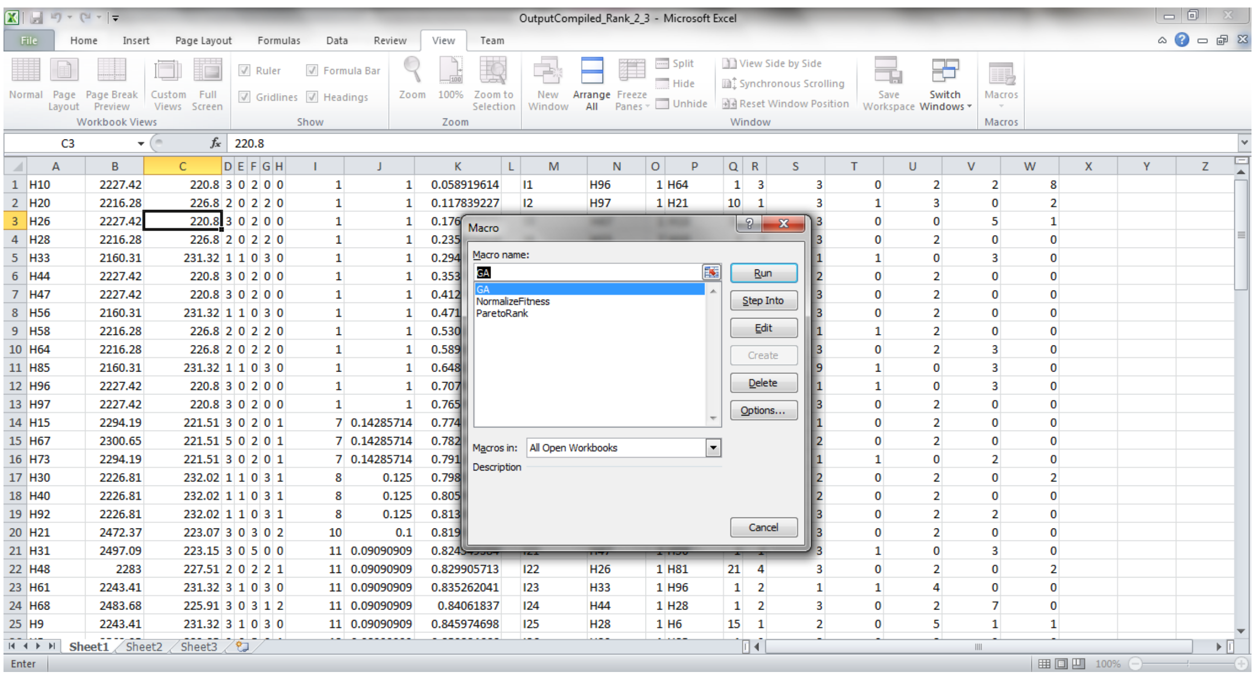

Figure 3.6. Screenshot of Excel Database

Step 3 through 5 were performed in Excel and automated using Visual Basic Macros. Seen in the screenshot of Figure 3.6, an automated algorithm was created to compile the data from the energy simulation output files, and one was created to give each solution a Paret-rank based on fitness. A final sub-routine was created to perform the sorting, selecting, reproduction, and mutation of the genetic algorithm.

Augmented Genetic Algorithm Process

For the augmented GA, most of the process remains true to the traditional process. In fact, Step 2 through Step 5 are identical to the steps outlined in the previous section. The only step that differs is the first. Rather than identifying 100 solutions at random for the initial population, this study suggests using a population set from a previous trial, regardless of whether the variables match exactly.

In this experiment, the final solution set of Trial 1 was used for the initial population of Trial 3. Since Trial 1 used single glazing as the window type and Trial 3 used double glazing as the window type, the Pareto rank of Trial 1 was not necessarily true for Trial 3. Therefore, the following steps were used to prepare the initial population set for Trial 3.

Step 1. The final population of Trial 1 had the Pareto rank removed.

Step 2. Construction costs of each solution were recalculated by substituting the cost of double glazing in lieu of single glazing. The amount of each material was known through energy simulation output data. This process was performed by a simple Excel macro.

Step 3. The solution set was re-ranked based on the revised construction costs. The energy use could not be easily recalculated, since that would involve performing an entirely new set of simulations. Therefore, the rank of the initial population does not truly reflect the optimization goals of Trial 3.

Step 4. The traditional GA process is started (see Step 2 of Section 3.2.2.)

One of the two fitness measures (cost but not energy performance) were included in the ranking method to prepare the initial population for Trial 3. So even though the actual Pareto-rank is not established for the beginning of Trial 3, the authors suggest that the solution set has already undergone "partial optimization."

The hope that this added starting measure will allow faster convergence on the global optimum because it is starts as more optimal than random. To analyze this hypothesis, Trial 3 is compared with Trials 2A and 2B. All three trials have the exact same variables, but Trials 2A and 2B are performed with initial random populations and act as controls for comparison.

3.1.3. Solution Indexing Method

The current research index process was mainly taken from a study that used GA's to investigate multi-objective façade optimization for daylighting design (Gagne & Andersen, 2010). The method used in that paper is straightforward: an external memory holds a set of *all* non-dominated solutions produced over the course of the process. A non-dominated solution is one that is more fit in at least one fitness objective than all other solutions. However, for the current research expanded upon that to index the *entire* set of all solutions in an external memory database. The reason for this is because the aim of the current study is to utilize past solutions for future energy modeling investigations. A non-optimal, dominated solution in one trial may be a Pareto-optimal solution in another trial, so all solutions are kept in a database and evaluated based on fitness for every trial. Figure 3.7 is adapted from a figure shown in the research of Gagne & Andersen (2010) and shows the GA process used in the current study combined with the external memory solution indexing.

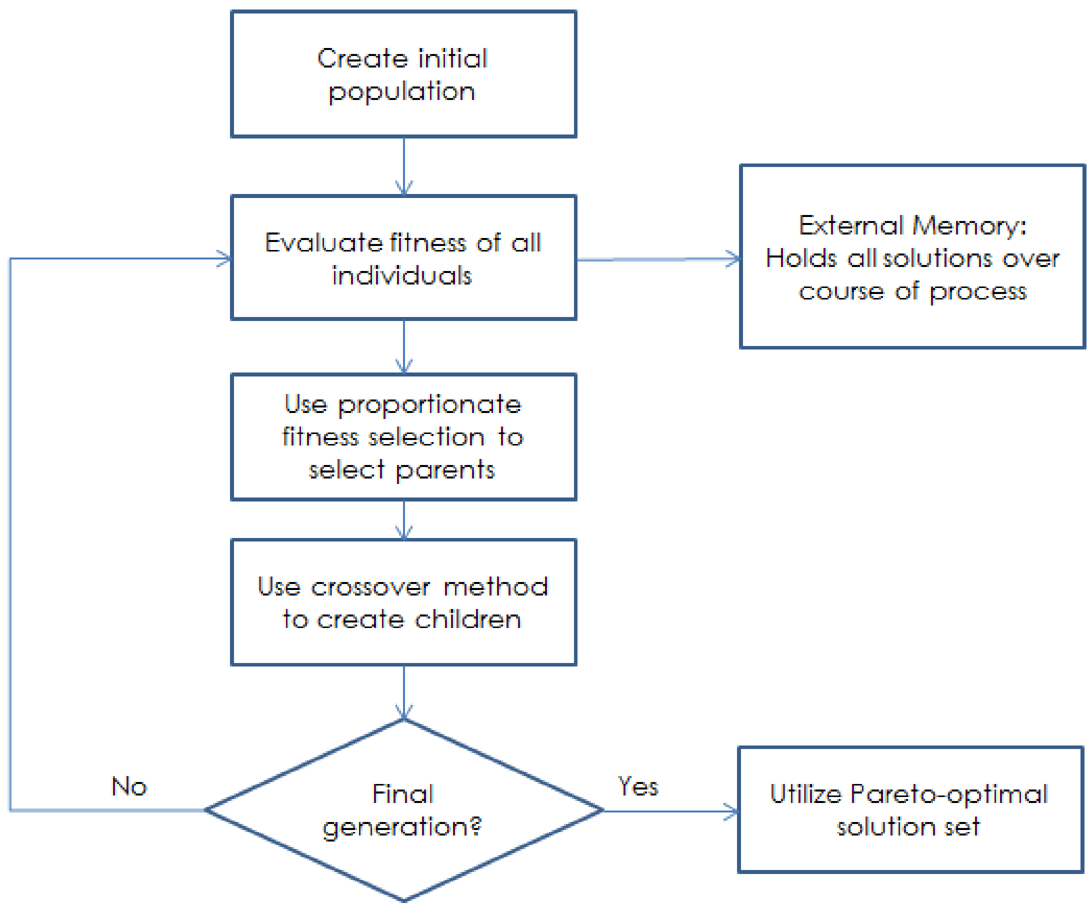

Figure 3.7. GA Process with Solution Indexing Adapted from (Gagne & Andersen, 2010).

Essentially, researchers have been attempting to index previously performed energy simulations into accessible databases. The goal is that even though each building problem is fundamentally different and has a unique design space, one can at least find a similar solution set to build upon. The initial solution space will then be optimized according to the specific design problem. If there is a large enough database established, then there can be a partially optimized solution set for every building condition. This current research couples the notion of indexing simulation results with seeding the initial GA population.

3.2. Research Framework

In order to investigate whether the augmented approach works, a traditional GA was employed using the fundamentals used in the research precedents outlined in the previous section. The remainder of this chapter outlines the specific parameters used in this study.

3.2.1. Genetic Algorithm Parameters

This thesis presents a similar approach to the study by Wang et al. (2005) as described in the literature review. While the basic features of that study were maintained in this research, the approach was simplified. The building optimization proposed in this experiment aims to minimize total energy use and cost. In this instance, however, the simplified metric of construction cost is substituted in place life-cycle analysis. The number of variable parameters explored in this study is also reduced to only including building orientation, glazing type, and percent glazing with the exclusion of other variables.

This paper's study executes a simple GA that follows Fonseca and Fleming's (1998) fitness assignment and population ranking based on proportionate fitness selection. With this method, a non-dominated solution is given a Pareto rank of 1. Dominated solutions are given a rank equal to the number of solutions that dominated it. The Pareto-rank algorithm used in this study was modeled after the pseudo-code described in Duh & Brown (2007) which states that dominance is defined by the existence of at least one solution that has at least one objective solution smaller than the current individual. Niche induction methods to promote population diversity were not performed in this study.

For the GA parameters used in this study, the work of Suga et al. (2010) was applied as a precedent. The lessons learned from their research were used to reduce the probability of improper convergence. Using their research as a guide, the population size used in this research experiment was set to 100, and the mutation rate used in this research was 5%.

The precedents described in this section have defined the framework and parameters that will be utilized in this thesis. See Table 3.1 below for a summary of the GA framework established in this section.

Table 3.1. Defined Genetic Algorithm Parameters

Operator	Method
Fitness Evaluation	Fonseca and Fleming's Pareto ranking method
Selection	Fitness proportionate selection
Population size	100
Crossover	Random single-point crossover
Mutation rate	5% mutation rate, mutates to a random parameter value
Fitness Sharing	None

3.2.2. Energy Simulation Fitness Goals

The two fitness goals defined in the multi-objective optimization are initial construction cost and total energy use. The units used in the construction cost estimate are in US dollars per conditioned building area in square meters ($/m^2). For conversion purposes, 1 m^2 is equivalent to 10.76 SF. The units used in the estimated annual energy use are net source energy in mega joules per conditioned building area in square meters (MJ/m^2). Although the majority of this research utilizes SI units, annual energy use will be converted to Imperial units in certain instances to for comparisons to other research. The Imperial equivalent is called *energy use intensity* (EUI), and is calculated in kBtu/ft^2.

Site energy is the amount of energy consumed by a building as reflected in measured power usage utility bills. *Source energy* is a "more accurate measure of a building's energy footprint, because it includes energy that is lost during production, transmission, and delivery to the building" (AIA, 2012).

3.2.3. Energy Model & Simulation Constants

The base energy model was initially created with the help of the online resource EnergyPlus Example File Generator developed and supported by NREL and the DOE (DOE, 2012). The file generator takes basic inputs for building information and creates necessary files for energy simulation. An example simulation is also performed through the online resource, and shape files are created for use with CAD software or OpenStudio. All of this information was then e-mailed to the researcher of this thesis.

The input provided to the file generator is outlined in Table 3.2. The dimensions of the building reflect standard thirty foot modules and 14'-0" floor to floor heights for inpatient hospitals. A traditional US calendar is used in terms of work week and holiday scheduling, and the lighting and heating/cooling schedules are based on typical healthcare operations. Many of the remaining inputs were left as default, with the understanding that the defaults would remain constant throughout all trials because consistent results were important for comparative analysis.

Table 3.2. EnergyPlus File Generator Input

Parameter	**Input**
Target Standard Performance	AHSRAE 90.1-2007
Units	English
EnergyPlus Version	EnergyPlus 7.1
Building Locations	Atlanta, GA
Building Type	Healthcare (Inpatient)
Number of floors	3
Orientation	0
Zone Layout	Perimeter and Core Zoning
Floor to Floor Height	14'-0"
Geometry Configuration	Rectangle
Length 1	30'-0"
Length 2	120'-0"
Roof Type	Insulation Entirely above Deck
Wall Type	Steel-Framed
Building Activity	Smart Default
Building Fenestrations	Smart Default
HVAC System based on	ASHRAE 90.1-2004 Appendix G Types
Outside Air	Smart Default
Service Water Heating	None
Photovoltaics	None

After receiving the example file, the EnergyPlus model was checked and revised based on the exact study. The Atlanta weather file was downloaded from the website for subsequent trials, and a city terrain input was identified due to its urban location. The material thermal and cost properties used in this study are the default ones that come with the Energy Plus package. The default percent glazing was 40% for each façade, but that parameter was changed to a variable parameter as explained later in this section. Figure 3.8 is a graphic representation of the test building shown in Google SketchUp using the OpenStudio plug-in.

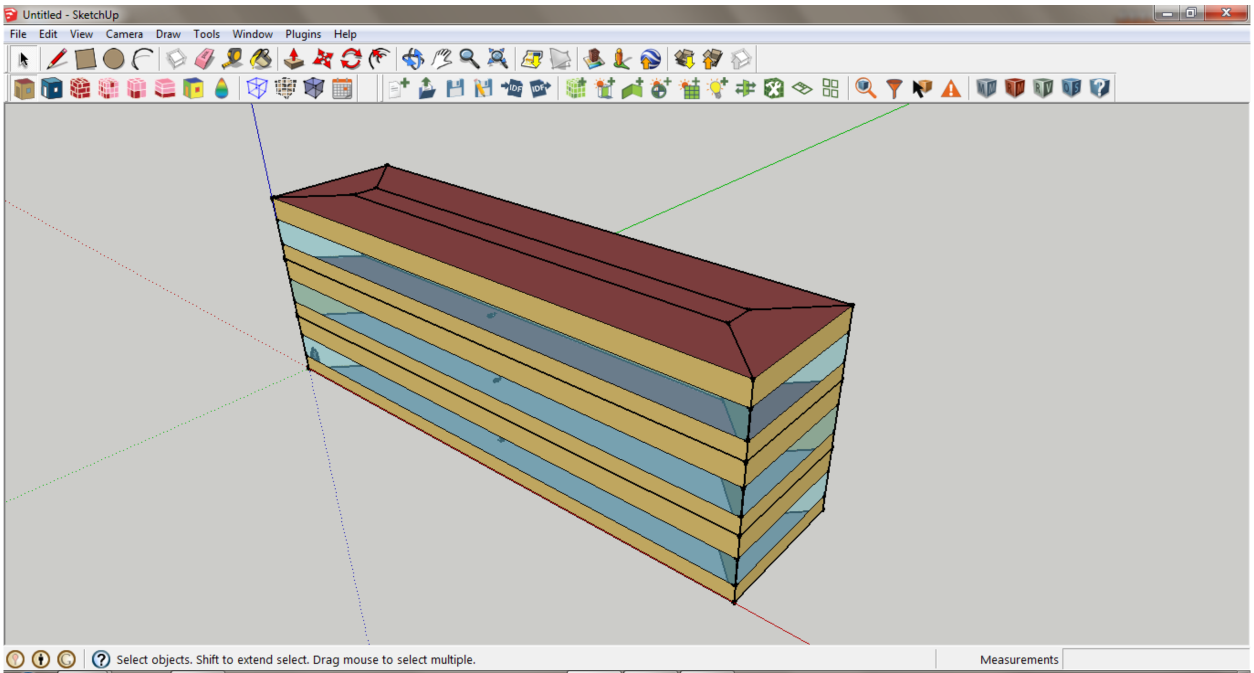

Figure 3.8. Building Geometry of Hypothetical Study Building.

3.2.4. Energy Simulation Variables

In order to be efficient and use the average computer system, the current research used far less design variables that the majority of works cited as precedents. There are a vast number of parameters that can be focused on, but for simplicity this research focused on five variable parameters. The simplicity used in this research is not anticipated to affect the validity of this study's claims, as the trials are tested against each other and not against other data. In addition, providing fewer variables will not make the energy simulations any less exact. A complete energy model is used for the test, and the simplicity is only pertaining to the amount of parameter variables established.

The five variable parameters used in this study are building orientation, percent of glazing on the north façade, percent of glazing on the east façade, percent of glazing on the south façade, and percent of glazing on the west façade. Each variable has ten possible values: orientation ranged from 0 to 45 degrees in 5 degree intervals, and percent glazing ranged from 1% to 90% for each façade. Each parameter has 10 possible values, for a total of 100,000 possible design solutions. Table 3.3 summarizes the possible parameter values.

Table 3.3. Research Variables.

Variable Parameter	**Possible Parameter Values**
Building Orientation (in degrees)	0, 5, 10, 15, 20, 25, 30, 35, 40, 45
Amount of North glazing (percent)	1, 10, 20, 30, 40, 50, 60, 70, 80, 90
Amount of South glazing (percent)	1, 10, 20, 30, 40, 50, 60, 70, 80, 90
Amount of East glazing (percent)	1, 10, 20, 30, 40, 50, 60, 70, 80, 90
Amount of West glazing (percent)	1, 10, 20, 30, 40, 50, 60, 70, 80, 90

As mentioned previously, one benefit of using GA's is the ability to simulate discrete variables. This is particular useful in building research because of the selection of material types and assemblies that could be used in various ways. For example, a brick façade and metal panel façade can be two variables used in a single optimization exercise. This particular research used discrete variables, however it is recognized that they could have substituted for continuous variables in this instance. It was the goal of the research to use a methodology using discrete variables, and so the variable chosen in this experiment were not allowed to be continuous or averaged.

In all, four trials were performed. The first trial (1) used a traditional genetic algorithm modeled after previous research. The glazing type for the first trial is single pane glazing. The second (2A) and third (2B) trials use the same process as the first trial, except with different parameter values. The glazing type used for these trials is double pane with an air gap. The third trial (3) also used the double glazed parameters, but had a seeded initial population seeded. Trial 3 was seeded with augmented results from trial 1, which was simulated using the single pane glass. Table 3.4 once again shows the research trials in a table format.

Table 3.4. Description of Research Trials

Trial Run(s)	**Description**
Trial 1	Single Pane Glazing Random initial population
Trials 2A & 2B	Double Pane Glazing Random initial population
Trial 3	Double Pane Glazing Seeded initial population

The portion of wall that was not glazing was defined as spandrel glass backed with 3 inches of insulation and an interior of ½" gypsum board sheathing. This made the perimeter wall conceptually a curtain wall system where the percent glazing can easily be changed through various panel spacing. The thermal effect of mullions of joint connections were not considered in this study.

Determination of Variables

The variables were determined through a conceptual framework that promoted a set of results based on simple prediction. In other words, the researcher used past experience to decide which variables would hopefully make for a productive study. In that vein, glazing insulation and reflective properties were heavily examined.

One study used as a model for glazing investigation researched the effect of building orientation and percent glazing covered by blinds for multi-objective cost and thermal optimization (Littlefair, Ortiz, & Das Bhaumik, 2010). The study showed that shading that covers glazing always produces a reduction of cooling demand and an increase in artificial lighting and heating. Although the cooling energy reduction could achieve upwards of 50% savings, the authors concluded that cooling savings need to be balanced against increases in heating and lighting energy use.

A second study focused on window type properties and surface area to perform multi-objective optimization on building retrofits (Asadi, da Silva, Henggeler, & Dias, 2012). Table 3.5 from this study was considered in articulating the glazing type and cost.

Table 3.5. Characteristics of Alternative Windows
extracted from (Asadi, da Silva, Henggeler, & Dias, 2012).

N	Type	Thermal transmittance ($W/m^2\,°C$)	Effective solar energy transmittance (%)	Cost (€/m^2)
1	Single glazing Typical glazing	5.10	85.00	34.08
2	2bl glazing Without thermal break Uncoated air-filled metallic frame 4-12-4	2.80	75.00	39.42
3	2bl glazing Without thermal break Uncoated air-filled metallic frame 4-16-4	2.70	75.00	40.31
4	2bl glazing Low-e window (with thermal break) coated air-filled metallic frame 4-12-4 NEUTRALUX	1.60	62.00	55.72
5	2bl glazing Window air-filled metallic frame 6-12-4 SOLARLUX Supernatural 70/40 Temprado	1.60	44.00	135.53

The following sub-sections outline the thought that went into deciding the glazing types based on their thermal and cost properties. In must be reiterated that ultimately these values are not important to the outcome of the study. The experiment of the study will look at comparing one optimization method against another, and these glazing variables will remain equal in all trials. Yet the current study can only be strengthened by presenting more or less realistic values for energy simulation purposes, and so great effort was made to find appropriate values for each parameter.

Glazing Thermal Properties

According to construction texts, the thermal resistance of a ¼" single pane of glass (RSI = 0.16) is approximately two times less than a 1" double paned glazing panel comprised of two ¼" glass panels and an air gap (RSI = 0.35) (Allen, 1999, p. 659). That information was recalculated and combined with data regarding spandrel glazing backed with R-10 insulation (California Energy Commission, 2006) to create Table 3.6.

The thermal properties found in Table 3.6 were deemed to have enough variation to provide a good design space of which to perform a GA.

Table 3.6. Thermal Insulating Values of Glazing Assemblies.

Material Description	**Thermal Insulating Values at center of assembly (U-Factor)**
Single pane glass, ¼" thick	6.29
1" Double pane glass, ¼" glass with air gap	2.84
Single pane spandrel glass with R-10 insulation between framing members	0.804

Ultimately, the values found in the EnergyPlus material libraries were used for the actual energy simulations. The glazing construction material library was used for the glass materials, the gas material library was used to define the air space, and the spandrel assembly combined materials found in the base EnergyPlus material library. Table 3.7 summarizes the EnergyPlus materials used in the study, and Table 3.8 lists the glazing properties defined by the EnergyPlus material libraries.

Table 3.7. EnergyPlus materials used for construction assemblies.

Construction	**Layer (Outside to Inside)**	**Material Definition**
Vision Glass (single glazing)	Layer 1	CLEAR 6MM
Vision Glass (double glazing)	Layer 1	CLEAR 6MM
	Layer 2	AIR 13MM
	Layer 3	CLEAR 6MM
Spandrel Glass	Layer 1	F09 Opaque spandrel glass
	Layer 2	I03 75mm insulation board
	Layer 3	GP01 ½ GYPSUM

Table 3.8. Glazing material properties defined in EnergyPlus.

Material Property	**SINGLE CLEAR 6MM**	**DBL CLR 6MM/ 13MM AIR**
U-factor	6.144	2.716
SC	0.94	0.81
SHGC	0.815	0.701
T_{sol}	0.775	0.604
T_{vis}	0.881	0.781

Glazing Cost Properties

Cost values of the majority of elements used in the EnergyPlus model were defined by the default values found in the program. Since the glazing assemblies were the variables, special attention was paid to get them as close to realistic as possible. For construction cost data, *RS Means Building Construction Cost Data 68th Annual Edition* (RS Means, 2010) was used as the standard metric. It was assumed that labor was to be equal for all applications, the 2010 bare material costs were entered as the associated material costs in the EnergyPlus model.

Table 3.9. Costs of Variable Building Materials

Material Assembly	**$/SF**	**$/m²**
Single glazing, ¼" thick	$5.35	$57.58
1" thick double glazed with two ¼" thick panes	$21.00	$226.04
Spandrel glass for non-vision areas, over 1,000 SF	$14.30	$153.92
3" rigid insulation	$0.40	$4.31

Notable to the study is that the spandrel construction assembly has a greater cost than single glazing but a lower cost than double glazing. Theoretically, this will mean that a solution involving single glazing will be more expensive the less glass it has. If thermal values are considered, however, more glass will mean less energy efficiency. Conversely, a solution involving double glazing will want to minimize glazing to reduce material cost. The theoretical optimization in that instance is not a straightforward, as the double glazing has considerably better insulating properties than the single glazing. Due to these fundamental dynamics, these were the variables considered in the current study.

3.2.5. Research Tools

The three primary computation tools used to conduct this research were Microsoft Excel, EnergyPlus, and jEPlus. Microsoft Excel was used as a database. Original Visual Basic macros were written and executed to process bulk sorting and filtering within the Excel program. EnergyPlus is a widely used and highly respected energy simulation software frequently used to estimate building energy use.

Unlike eQuest, the energy modeling program described in this research's literature review, EnergyPlus is purely a simulation engine that analyzes numerical data. The program has no user interface, although some minimal applications come with the program download. While eQuest may be easier for firms looking at 3D models and using energy wizard guidance to create energy models, EnergyPlus can efficiently use non-graphical data to perform simulations. Because this research will be running large amounts of simulations, simple data inputs and outputs were preferable.

jEPlus works in conjunction with EnergyPlus as a front-end, Java application that batch processes large numbers of energy simulations. Because energy analysis is completely impacted by how results are derived, and this thesis relies heavily on energy simulation results, both EnergyPlus and jEPlus will be described in detail.

EnergyPlus

The EnergyPlus program began development by the DOE in 1995, but was not the first iteration of building simulation software. In fact, whole-building simulation has been used for over 30 years, and researchers have "long used such tools to represent large portions of the building stock" (Griffith, et al., 2008).

For more than 20 years prior to 1995, "the US government supported development of two building energy simulation programs, DOE-2 and BLAST." After many complaints of the inefficiency involved with having two parallel, and similarly capable and compatible, programs supported by the government, a forum was held in 1995 regarding the issue. In 1996, the DOE took the initiative to develop a new energy simulation program. This new program was EnergyPlus and the project team includes: US Army Construction Engineering Research Laboratories (CERL), University of Illinois (UI), Lawrence Berkeley National Laboratory (LBNL), Oklahoma State University (OSU), GARD Analytics, and DOE (Crawley, et al., 2001).

EnergyPlus combines the best capabilities and features from both DOE-2 and BLAST, as well as adds additional features (Crawley, Lawrie, Pederson, & Winkelmann, 2000). EnergyPlus works by simulating building performance at predetermined time steps. The results for each step are aggregated in simple data files that easily allow users to "access specific results without modifying the calculation engine." The output results are also formatted in standard file formats so they can be readily opened in common database and CAD applications (Crawley, et al., 2001).

An important feature of EnergyPlus is that it has extensively and continually been evaluated in terms of simulation accuracy through comparative and analytical testing (Crawley, et al., 2001). One study of twenty major building energy simulation programs found EnergyPlus had most of the capabilities tested by the study, and more capabilities than the majority of other programs under review. The study highlighted EnergyPlus' integrated solutions by stating that they provide "more accurate space temperature prediction – crucial for system and plant sizing, occupant comfort and thermal health calculations." These integrated solutions, the authors suggest, also allow users to evaluate realistic system controls, radiant heating and cooling systems, and other features (Crawley, Hand, Kummert, & Griffith, 2005).

There is no formal user interface for EnergyPlus, as it is primarily a simulation engine (Crawley, Lawrie, Pederson, & Winkelmann, 2000). Today EnergyPlus does come with user interface add-ons such as EP-Launch and IDF Editor, used to perform simulations and update simulation files, respectively. The program is currently available to download for free at the DOE website (US Department of Energy, 2012).

Third-party applications have also been developed to provide more intuitive user interfaces for the EnergyPlus simulation engine. One of the most popular third-party add-ons is developed by NREL and is called OpenStudio. The OpenStudio program provides a versatile graphic interface for EnergyPlus and can be used as a plug-in for the 3D modeling software Google SketchUp. The ability to create EnergyPlus models with a simple modeling program like SketchUp has expanded the availability of utilizing the powerful simulation engine of EnergyPlus to less advanced computer users. OpenStudio and the OpenStudio SketchUp plug-in can also be downloaded for free online (NREL, 2012).

EnergyPlus Applications

EnergyPlus has been used in a variety of research studies. A significant number of those studies also include the use of genetic algorithms for energy efficient optimization. This paper highlights some of those studies that contain both GA and energy analysis as they are pertinent to this research topic.

One study performed in 2011 combined EnergyPlus simulations with an evolutionary neural network design to design energy efficient building facades (Zemella, de March, Borrottid, & Poli, 2011). Many authors combine the use of GA's with dynamic controls to study optimal energy reduction through automatic systems in this manner. Another research article published in 2012 combined GA's with artificial neural networks to optimize chiller operation in office applications. The authors of that paper also used EnergyPlus to perform their simulation trials (Congradac & Kulic, 2012).

Both of these examples of using EnergyPlus as a simulation engine combined with evolutionary optimization were deemed successful, but authors Congradac & Kulic (2012) took their validation a step further. They combined their simulation results with data compiled from a series of real-world experiments performed on constructed office buildings to verify their findings.

Other studies also compare EnergyPlus applications to real-world situations. One study commissioned by NREL investigated EnergyPlus results as compared to data from the 2003 CBECS commercial building survey. The research team modeled a large population of EnergyPlus models based on the building characteristics from the 2003 CBECS data in order to ask the question: "How well do results from a set of EnergyPlus models for the whole sector agree with 2003 CBECS?"

In total, the results from 4,820 models were compared with the 2003 survey in terms of site EUI. The NREL findings concluded that there was an overall agreement of 12% between the simulations and the real-world data, a level "deemed acceptable given the level of scatter in the survey data" (Griffith, et al., 2008). The specific outcomes regarding the healthcare sector will be discussed in the Research Challenges sub-section of this chapter.

jEPlus

jEPlus is described by its developers as a "convenient tool for managing large and complex parametric simulations." Essentially, jEPlus is a simple tool that allows users to describe multiple parameters and parameter values for EnergyPlus simulations, and then automatically creates and performs those EnergyPlus simulation jobs (Zhang & Korolija, Performing complex parametric simulations with jEPlus, 2010).

jEPlus Applications

The jEPlus program has been utilized in a number of studies that want to explore large numbers of simulations, which makes the program well suited for GA optimization. One study demonstrated that concept explicitly by conducting experimental trials of both single and multi-objective optimization problems using jEPlus coupled with GA framework. The authors of that study summarize: Once the optimization scheme decided and search space defined within a jEPlus project, the GA can be "coupled with jEPlus to perform optimization." All necessary input and output files for running the EnergyPlus simulations are referenced by jEPlus (Zhang, 2012).

3.3. Research Implications and Limitations

Research Implications

As mentioned previously in this thesis, the implication of the proposed research is the possibility of a more efficient optimization process that can adapt to the fast-paced and fluctuating world of building design and construction. Given the goal of this research is to develop a reasonably accurate set of optimal solutions without specialized computer resources and within a practical timeframe, the successfulness of this experiment can be conceptually significant toward the practices of building design and construction optimization.

The benefits of using "best fit" initial solutions from a cumulative index have the possibility to make a much more efficient genetic algorithm. For example, even the small index sample created from this experiment could possibly benefit future energy optimizations that pertain to healthcare buildings, building located in a similar climate to Atlanta, or even dissimilar building types of the same general shape. If those future simulation results are also compiled into the index, the database will become even more robust. The larger the index, the more common characteristics can be found in any potential building problem to apply "best-fit" initial solutions.

If utilized on a large scale, the index database can accumulate data relating to all aspects of the buildings, not just energy use and construction cost. In addition, the building parameters and information stored in the database can combine real-world data, simulation data, and other database information. All of these possibilities combined have the potential to lead to a continuous optimization process where all phases of design and construction can be optimized starting with a "best fit" set of solutions that pertain to the current design problem. Subsequently, all outcomes and results from those analyses will be added to the cumulative database. Figure 3.9 shows a conceptual diagram of this process.

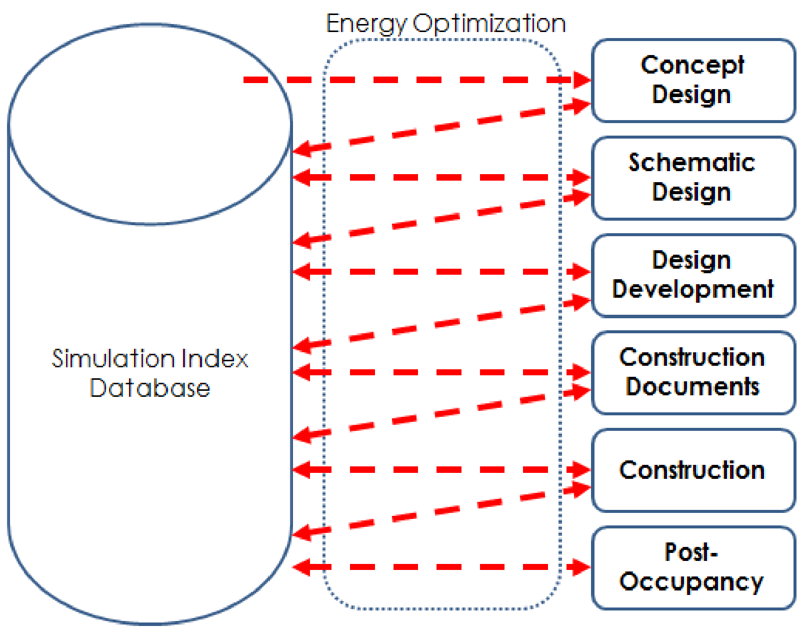

Figure 3.9. Conceptual Framework for Continuous Optimization using Index Solutions

Another potential impact this research has on the building design process concerns the relative speed of gaining potential results. A practical problem outlined earlier in this research explained the delay in getting energy model results in time to affect the building design and construction process. The proposed approach of this research has the potential to combine efficiency with cumulative results to branch out optimization exercises and run them in parallel as the building design progresses.

Figure 3.10 shows how the cumulative optimization trials can be expanded upon and run in parallel during the design and construction process. The practical application of such a feature would occur when the design parameters change during the building design phases. For example, an additional construction material may need to be added to the evaluation after the schematic design phase. Another example is if potential parameter values in initial optimization trials are reduced or expanded upon in subsequent phases. These optimization trials will continue with the more solidified parameters, but they will also be still analyzed against the cumulative index for comparison.

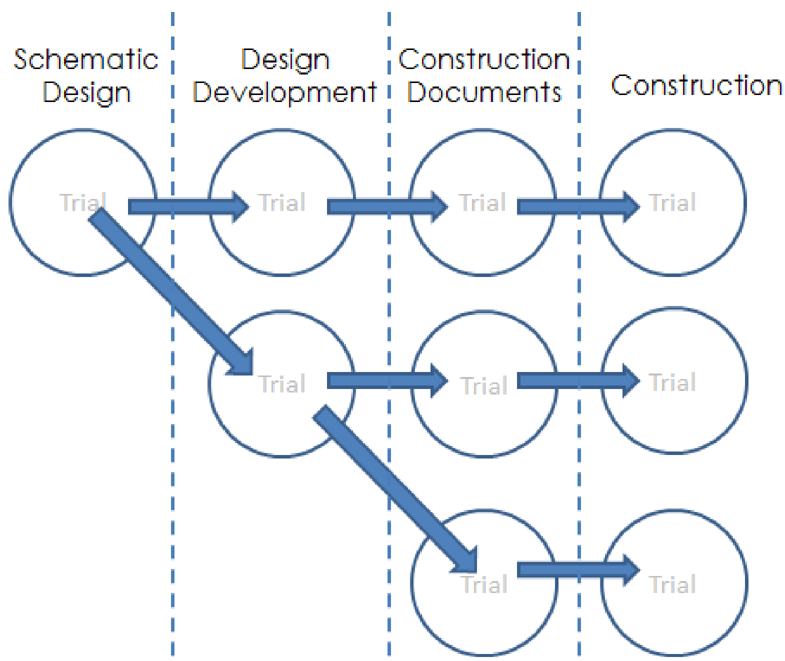

Figure 3.10. Conceptual Branching of Optimization During Design Process

Research Limitations

I addition to speaking of the potential beneficial implications of this research, it is equally important to recognize its limitations. The weakness of this research mainly resides in the reduction of scope and relying on comparative analysis over a complete and absolute analysis.

The minimization of this experiment to four trials is inadequate to fully test the implications of this proposed approach, and therefore any results should be considered initial indicators rather than conclusive evidence. The reduction of design problem into so few variable parameters also limited the ability to test the augmented algorithm. The other known drawback of chosen parameters is that they are continuous values of orientation and percent glazing that have been converted into discrete values.

The results and analysis in the following chapters are only valid for general comparisons in terms of both optimization time and cost, and optimal solution accuracy. This is because the scope of this research did not include in depth computer analysis of computation time or exact optimization performance. This research also did not use a "brute force" method or other methods to determine the actual global optimal solutions for each trial.

For the purposes of this research, a reasonable optimization time period was generally one that an average computer user could accomplish in one business day. The optimal results were compared against each other and not analyzed for their actual effectiveness. While these aspects are worthwhile of study, they were not considered in this research and regarded as beyond the scope of this thesis study.

CHAPTER 4: RESULTS

4.1. General Results

In general, the trials were conducted without incident. Each trial of five generations took approximately one day to set up, run, and compile data.

Every simulation in the current experiment took approximately 70 seconds on average to complete if run individually. The authors of one of the studies mentioned in the literature review (Zhang & Korolija, 2010) calculated that each simulation took an average of 83.69 seconds to perform, which aligns fairly well with each simulation run on this researcher's personal computer.

With jEPlus, the simulations were batch-processed in a staggered manner, with a maximum of four simulations running simultaneously, due to the simulated four-core limitation of the personal computer. When run with jEPlus, the batch computation of each generation took approximately 90 minutes, and so a total trial of five generations took almost 8 hours of computation time. This meant that each trial of 5 generations for this experiment took 8 to 10 hours, including the manual and semi-automated pre- and post-processing and sorting of data.

In summary, the current research was highly cognizant of computational time due to the precedent studies and ensured that the number of variables used could be accommodated without special computer clusters. Each trial run was performed over the course of one day, for a total of four days of computation time. Yet four trials are not necessary in real-world applications, they were conducted for comparison and analytical purposes. In practice, each building will only require one trial to find Pareto-optimal design solutions for energy analysis, and one day seems reasonable to accomplish this task.

As demonstrated below, Trial 1 was able to find a large amount of Pareto-optimal solutions within the design space. Trial 1 also enjoyed a smooth Pareto-curve and a rather evenly distributed variety of design solutions within the population. Trials 2A, 2B, and 3 were not as fortunate. There seemed to be a small number of Pareto-optimal solutions, and the design solutions were fairly striated. These trials also seemed to not enjoy as broad of a design space to work with.

These initial observations suggest that the variables of building orientation and amount of glazing do not have the same impact when the window type is a double glazing system rather than a single glazing system. This intuitively makes sense, as the thermal insulating properties and costs of double glazing are closer in both respects to the non-vision spandrel system comprising of the rest of the building. With less distinction between the window and non-window systems, there is less variation in energy and cost results which in turn shrinks the potential design space.

Optimization exercises are not immune to performing on non-ideal problems, and a well-functioning GA process will be able to function whether or not the solution space is beautifully diverse and provides a smooth Pareto curve. In that respect, the GA utilized in the current study seemed to perform satisfactorily in every trial.

Benchmark Trial

To begin the study, the initial Energy model was simulated with the constraints described in Trial 1. The variable parameters were assigned values of a building orientation of zero degrees and 40% glazing on all four facades. This single performance was to provide a benchmark simulation run and to assess whether the results were reasonable. The energy model was assumed to be strong if the simulated results were reasonably close to standard energy performance data.

After the simulation was performed, the estimated annual energy use was converted into kBtu/SF/year in order to assess EUI. The EUI of the single simulation was 301.69 kBtu/SF/year. The EnergyStar Target Finder (Energy Star, 2012) found the median hospital within the Atlanta climate area to have a source energy EUI of 428 kBtu/SF/year and a site energy EUI of 202 kBtu/SF/year. Another study found baseline site energy EUI in the Northwest United States to be from 260 to 270 kBtu/SF/year (Burpee & Loveland, 2010). These results are deemed in the acceptable range with no red flag showing any major flaw with the energy model set up.

4.2. Results from Trials

Each trial produced a large number of output files and results. This section highlights the findings of each trial. Specifically, each trial will show a graph that indicates the Pareto-optimal curve for its first generation and its last generation. These graphs are intended to illustrate the nature of each design space. Secondly, the progression of Pareto-optimal solutions is illustrated in a graph for each of the trials. These are the ideal diagrams that show convergence toward an optimum. Finally, each trial includes a graph that indicates the Pareto-optimal set of the external population index. Descriptions of noteworthy results are also included where applicable. Appendix B includes the results from all trials and generations for reference.

4.2.1. Results from Trial 1 (Base Experiment)

Graphically, the initial population for Trial 1 generation 1 appears to have a good distribution of the design space (see Figure 4.1). Of the 100 solutions, 14 were unique non-dominated solutions that create the Pareto-front.

As the graph demonstrates, Pareto-front begins to uncover the nature of the design space, even only after the first generation. The median optimal solution appears to hover around \$150/m^2, where the energy performance varies but the cost remains largely the same. Because this research did not use the “brute force” method of simulating all possible solutions, it is not known what the true optimal solutions are.

For the solutions where energy use is below this threshold, the cost is shown to increase proportionally with the decrease in energy use. Conversely, the solutions with energy consumption greater than that threshold have less of an effect on the solution cost, which remains largely in the same range for those solutions. These findings are in line with the research expectations.

For each successive generation performed for Trial 1, more non-dominated solutions were uncovered. Generations 1 through 5 had 14, 21, 21, 33, and 42 unique Pareto-optimal solutions, respectively.

As Figure 4.2 shows, the Pareto-curve becomes smoother and more complete after 5 generations. The results are also visibly less striated for the final generation. The design space observations from the first generation are still generally true, and the extents of the original search space remain more or less the same.

Figure 4.3 illustrates the Pareto-front progressing toward more global solutions over the course of each generation. Figure 4.4 shows the results of all five generations combined and given a Pareto-rank relative to the entire external indexed population. When the entire indexes of all generations were ranked, the result was 52 total unique, non-dominated solutions. Of those non-dominated solutions, 1 was a solution originating from the first generation's population, 7 were from the second generation, 10 were from the third, 16 were from the fourth, and 18 were from the final generation. Figure 4.4 also shows the solutions with a Pareto-rank of 2 and 3. These can be thought of as second and third-level tiers of optimality. Pareto-optimal, non-dominated solutions were given a rank of 1.

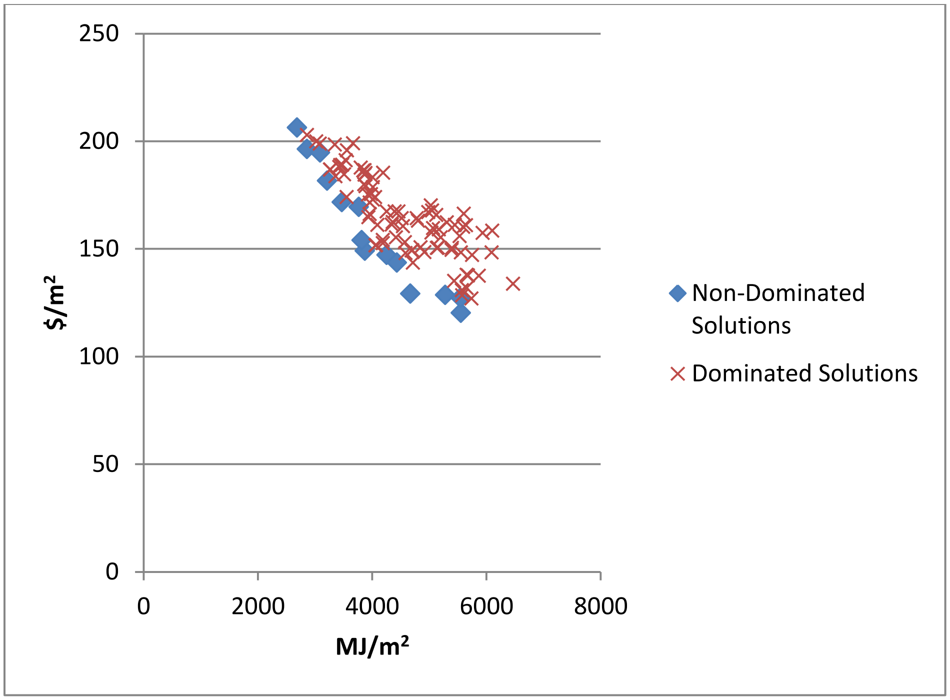

Figure 4.1. Trial 1 Generation 1 Results

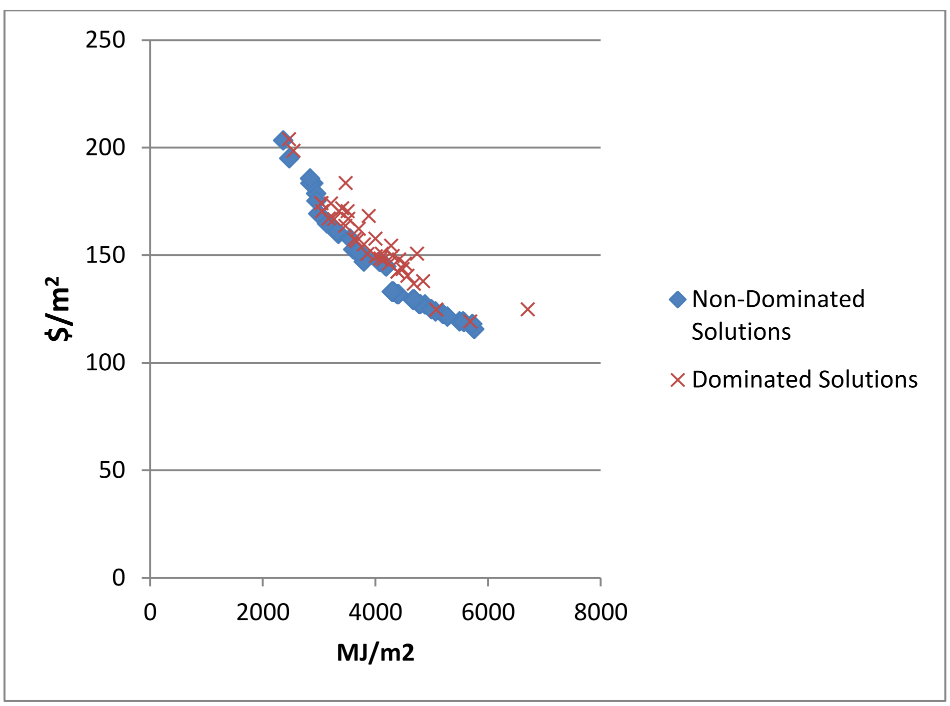

Figure 4.2. Trial 1 Generation 5 Results

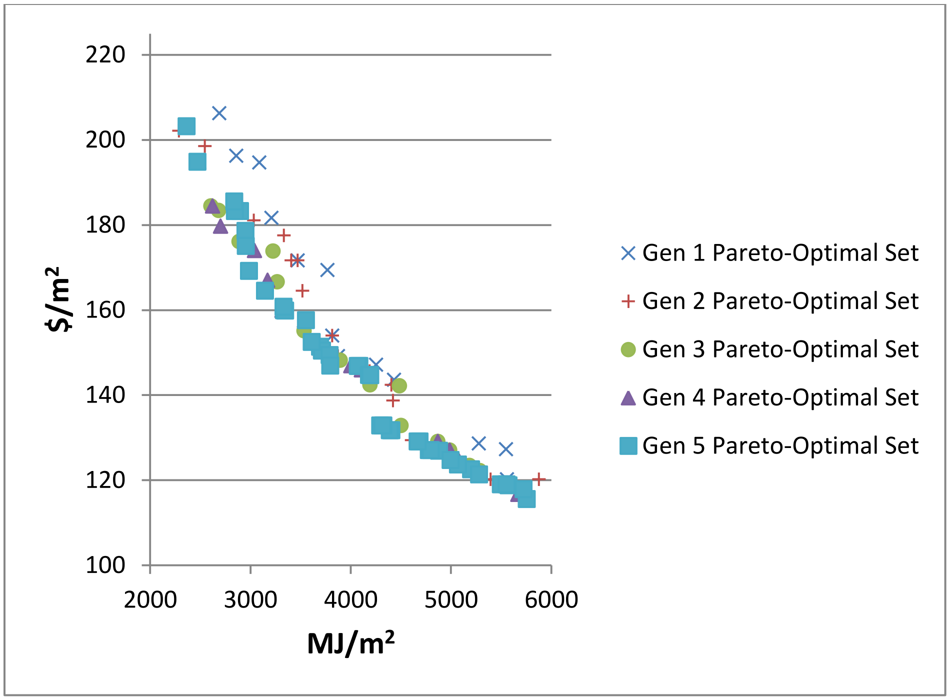

Figure 4.3. Trial 1 Pareto-optimal Results Across 5 Generations

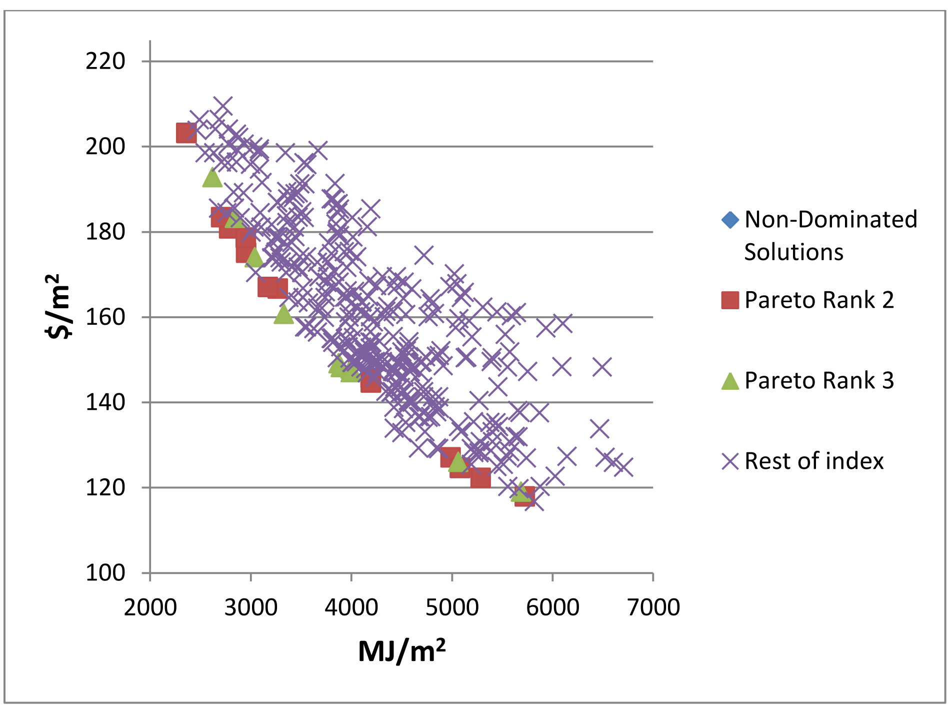

Figure 4.4. Trial 1 Pareto-optimal Curve of External Index

4.2.2. Results from Trials 2A & 2B (Controls)

In stark contrast to the easily legible generation 1 results in the first trial, Trials 2A had a largely dense first generation where the design space is graphically obscured. As seen in Figure 4.5, all of the results fall into a narrow range of cost with the exception of one outlier. The range of energy use varies greatly, and the cost is minimally reduced as the energy use decreases. The reason for this variability remains unknown.

The one major feature of the design space that the initial generation sheds light on is the relationship of fitness values for cost and energy usage. While Trial 1 saw a Pareto-curve that insinuated cost and energy efficiency were conflicting goals, the first generation of Trial 2A immediately illustrates that the two goals are in alignment for those sets of parameters. As the energy use decreases, the cost also seems to decrease.

However, as more solutions from the design space are found, as seen in Figure 4.6, the picture changes. The final generation again indicates conflicting goals. As energy use decreases, the cost increases dramatically. Therefore, the goals are in fact still conflicting, and the first generation simply did not uncover the true Pareto-front.

Each successive generation uncovered more Pareto-optimal solutions, but not nearly as many as Trial 1. For Trial 2A, the unique, non-dominated solutions were 2, 2, 3, 8, and 8 for generations 1 through 5, respectively. The final generation indicates a clearer picture the design space.

Figure 4.6 also is telling, as it shows the non-dominated solutions becoming drastically more optimal for each generation. In fact, no solutions in generations 1 through 4 dominate the Pareto-optimal set from the final generation's population. The 8 unique, non-dominated solutions shown in Figure 4.7 against all solutions in Trial 2A came from the last generation. That graph also differentiates the solutions with a Pareto-rank of 3. No solutions had a rank of two when compared against the entire external index population.

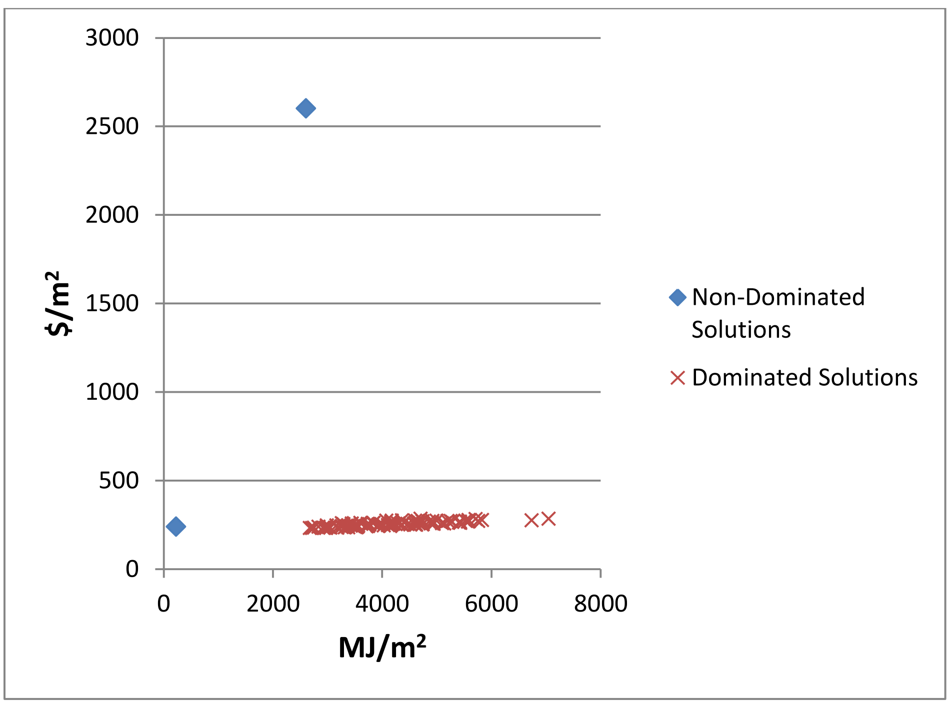

Figure 4.5. Trial 2A Generation 1 Results

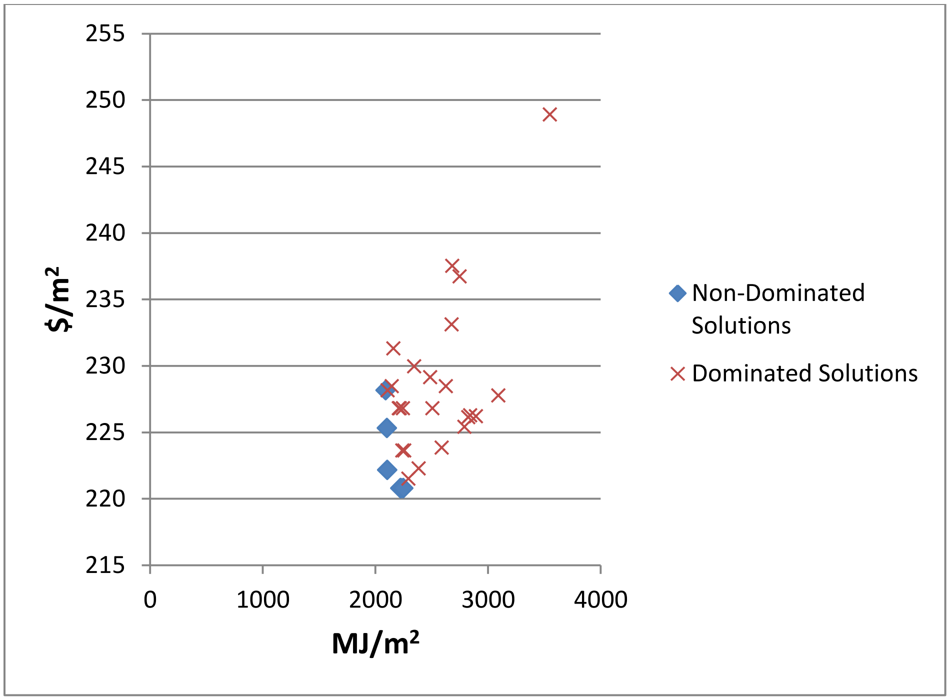

Figure 4.6. Trial 2A Generation 5 Results

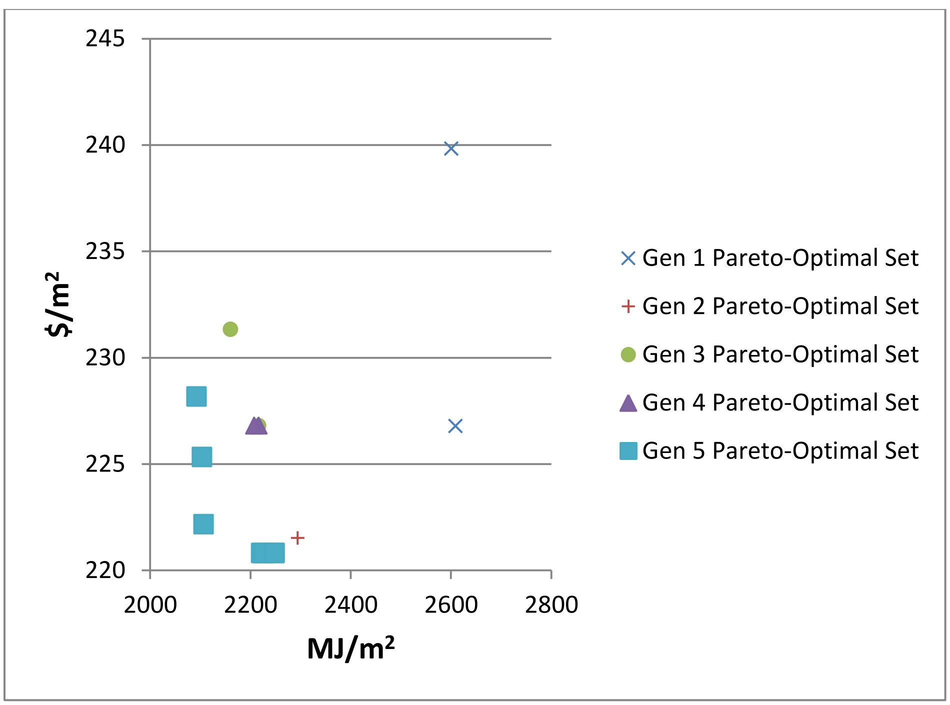

Figure 4.7. Trial 2A Pareto-optimal Results Across 5 Generations

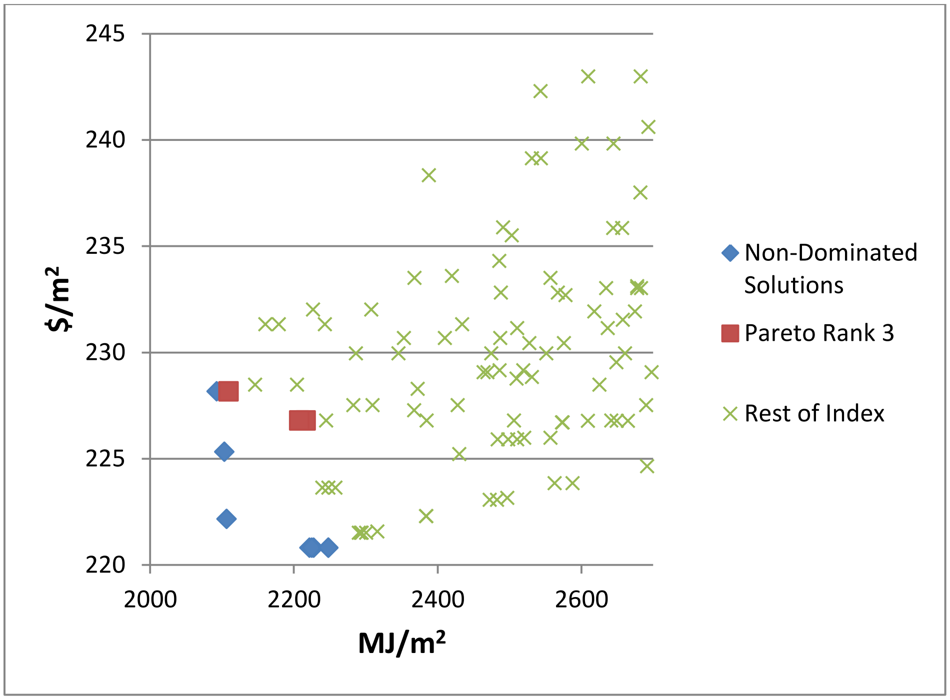

Figure 4.8. Trial 2A Pareto-optimal Curve of External Index

Trial 2B also showed an interesting design space in its first generation, but in a different manner. Only one non-dominated was discovered from the initial population, but the design space had much more diversity than discovered in Trial 2A. Like Trial 2A, the first generation graph of Figure 4.9 seems to indicate fitness goal agreement. As the cost decreases, so does the energy use. Like Trial 2A, that initial reaction is simply due to the lack of optimal solutions found during the first generation (see Figure 4.10).

The results from Trial 2B did not demonstrate a progression of non-dominated solutions like the previous two trials. The number of unique, non-dominated solutions fluctuated from 1, 3, 1, 5, and 8 from generations 1 through 5, respectively.

In addition, the results converged quickly, as evidenced in Figure 4.11. The cost fitness evaluation did not get improved after generation 3, and all of the non-dominated solutions are bunched together. Of the total 8 unique, non-dominated solutions compared to the entire trial solution set, 1 was from the third generation, 4 were from generation 4, and 4 from the final generation (see Figure 4.11 and Figure 4.12).

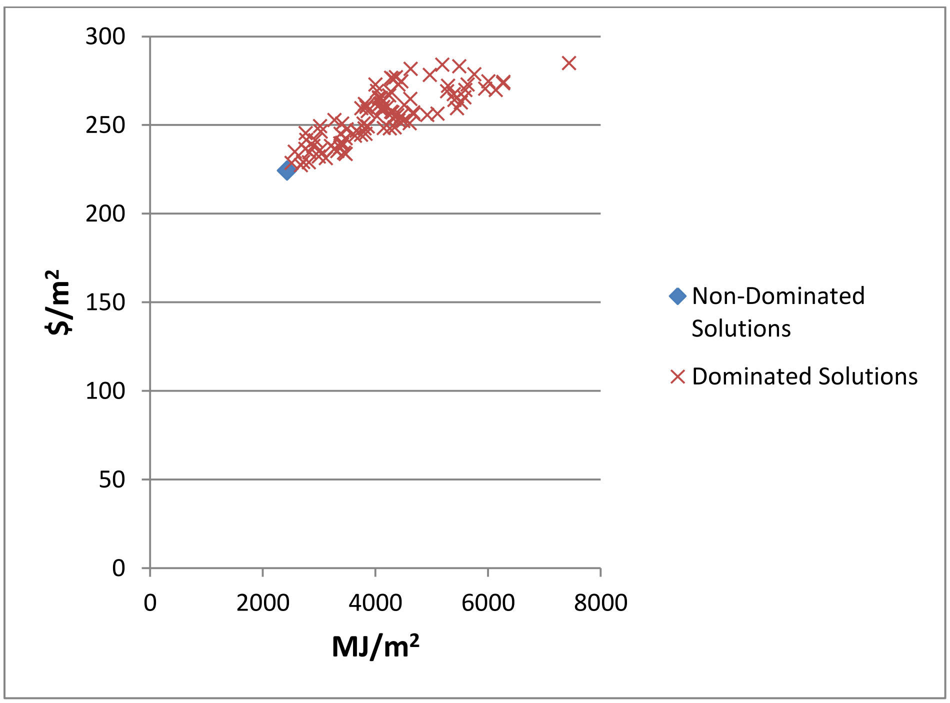

Figure 4.9. Trial 2B Generation 1 Results

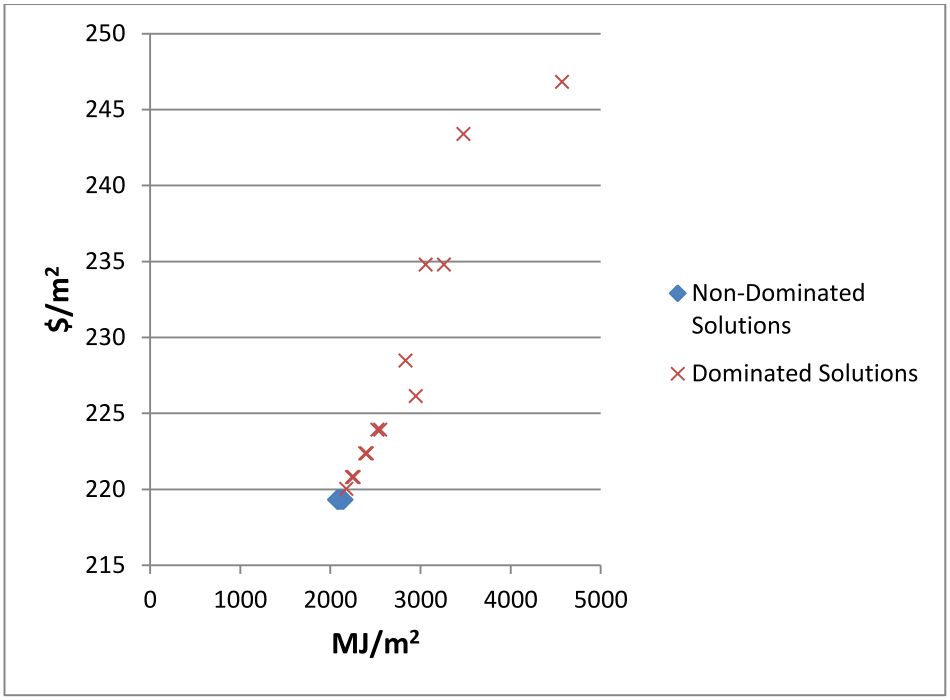

Figure 4.10. Trial 2B Generation 5 Results

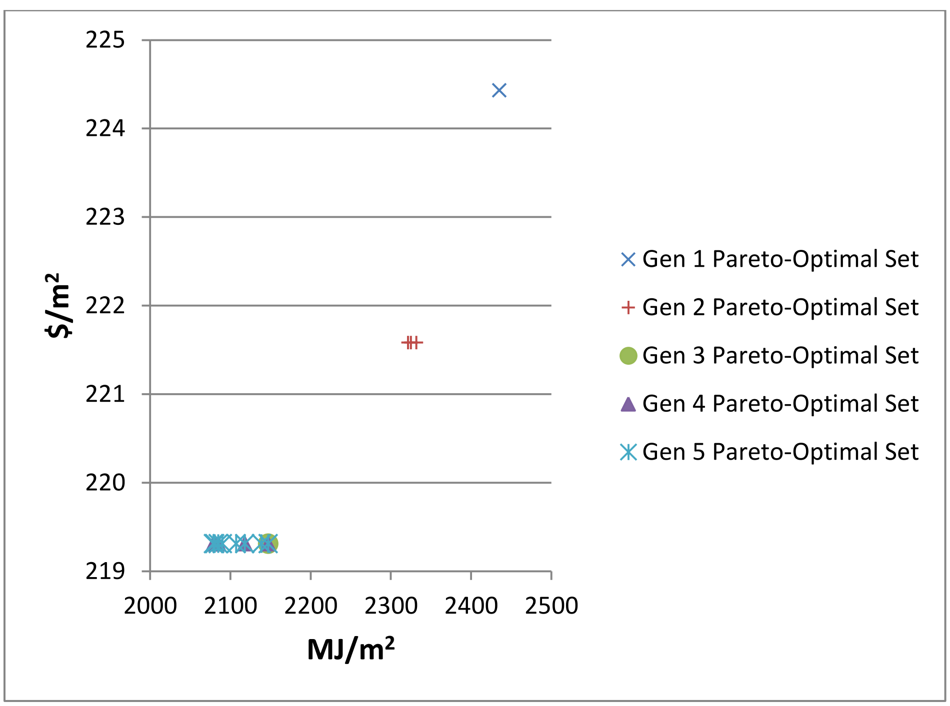

Figure 4.11. Trial 2B Pareto-optimal Results Across 5 Generations

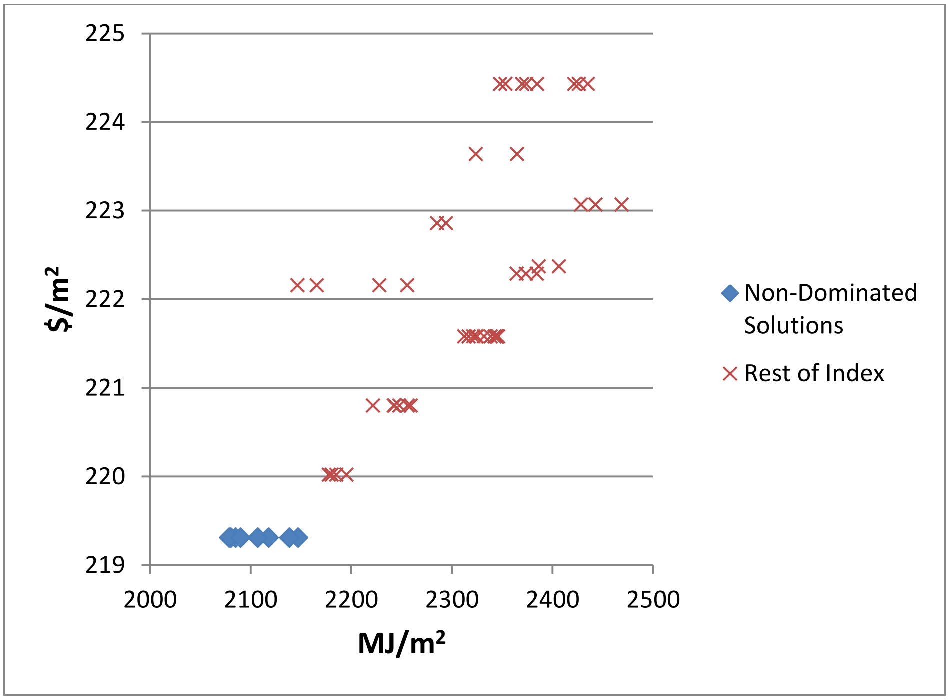

Figure 4.12. Trial 2B Pareto-optimal Curve of External Index

One reason for having two controls was to ensure a reasonable control for comparative purposes. The other reason was to evaluate convergence. Figure 4.13 compares the non-dominated solutions from Trial 2A and Trial 2B's entire set of solutions. Trial 2B has an obvious advantage in results, with all of its non-dominated solutions performing better than Trial 2A in terms of cost. Trial 2B also has solutions that minimize cost better than Trial 2A.

Such a set of trials fully demonstrates the variability of using stochastic methods for evaluating a design space. Whereas Trial 2A was not able to converge fast enough to find truly optimal solutions after 5 generations, Trial 2B converged on more optimal solutions after just 3 generations.

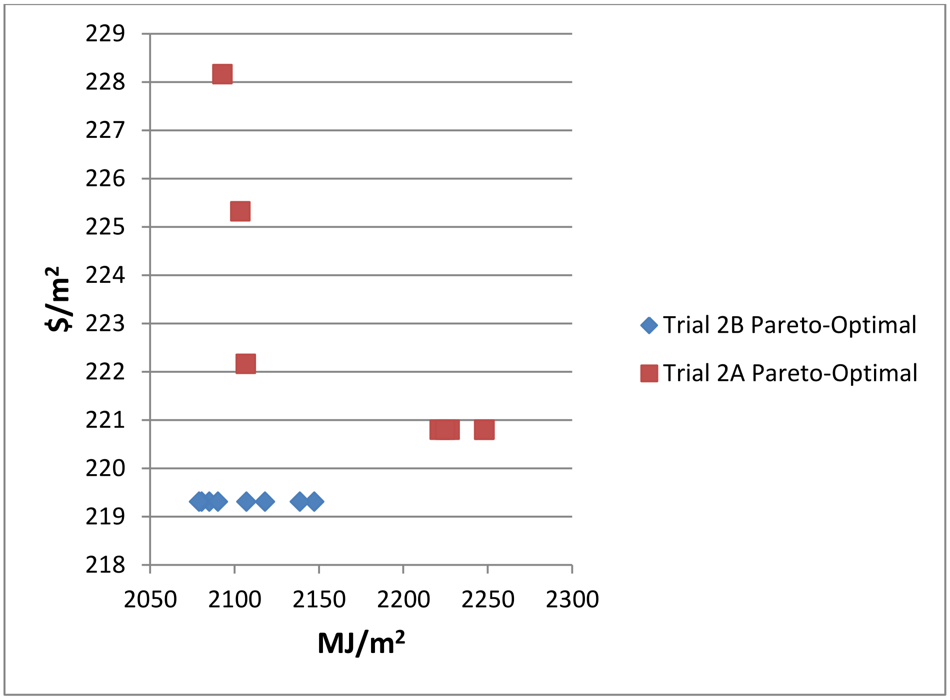

Figure 4.13. Comparison of Pareto-optimal Results for Trials 2A & 2B

4.2.3. Results from Trial 3 (Augmented Experiment)

The initial population of Trial 3 graphically shows good distribution of all solutions, with a Pareto-optimal set of 7 unique solutions (see Figure 4.14). The progression of unique, non-dominated solutions was from 7 to 2, 9, 9, and 9 for generations 1 through 5, respectively. While the final generation of Trial 3 had 9 non-dominated solutions, more than that of the final generations of either Trial 2A and 2B, the number of other unique solutions was small. This is the reason that the final generation of Trial 3 appears to have a scant population as illustrated in Figure 4.15.

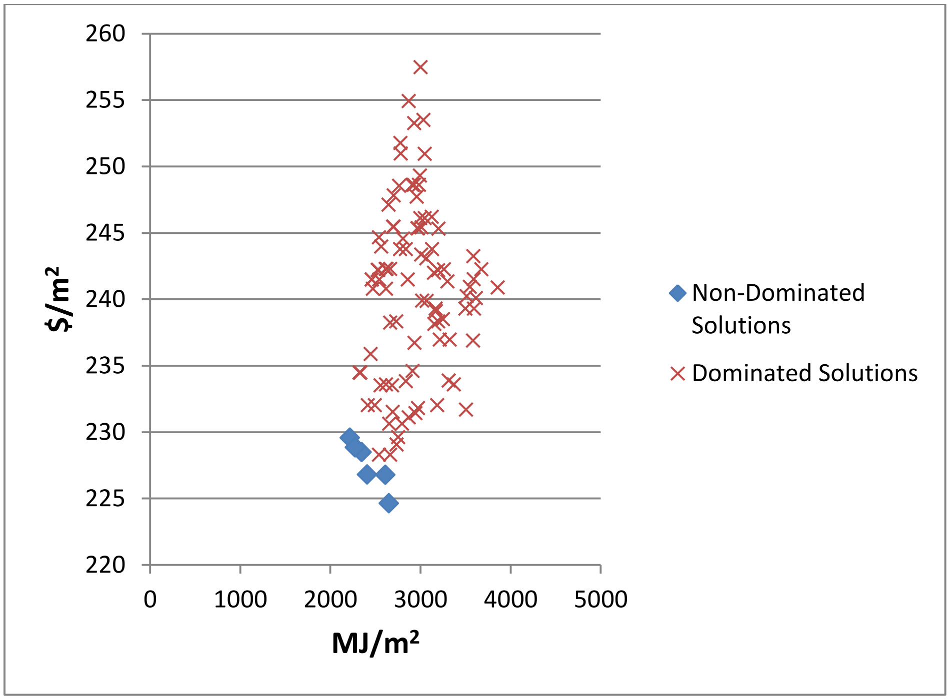

Figure 4.14. Trial 3 Generation 1 Results

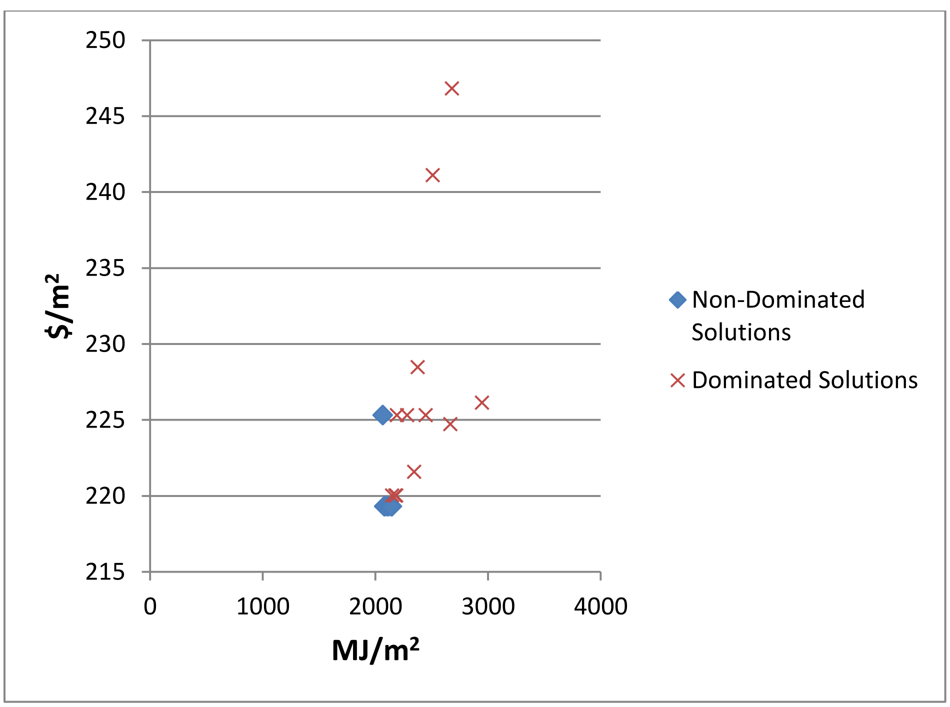

Figure 4.15. Trial 3 Generation 5 Results

Figure 4.16 shows a big leap in non-dominated solutions from the first to second generation of Trial 3. However, the Pareto-front barely moved after converging on that design space after generation 3. Figure 4.17 demonstrated the Pareto-optimal solutions of Trial 3 when analyzed against the indexed population of the entire trial. Of the 7 ultimate non-dominated solutions in that population, none come from the first or last generation. 2 originated in the second generation, 3 in the third, and 2 more in the fourth. This is the first time we have seen a final trial generation not producing at least one new, unique non-dominated solution.

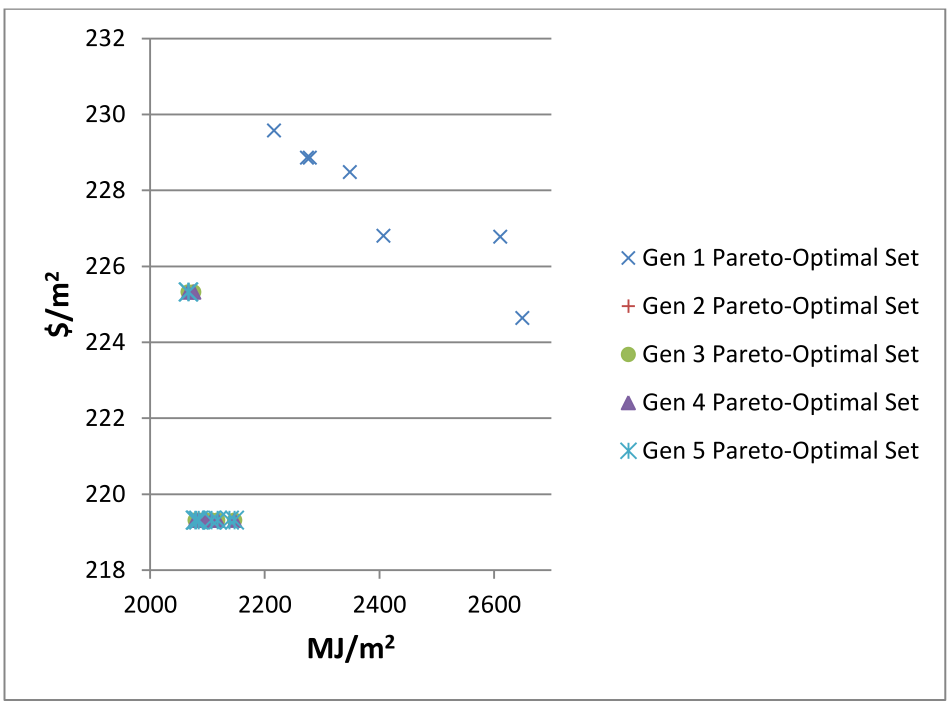

Figure 4.16. Trial 3 Pareto-optimal Results Across 5 Generations

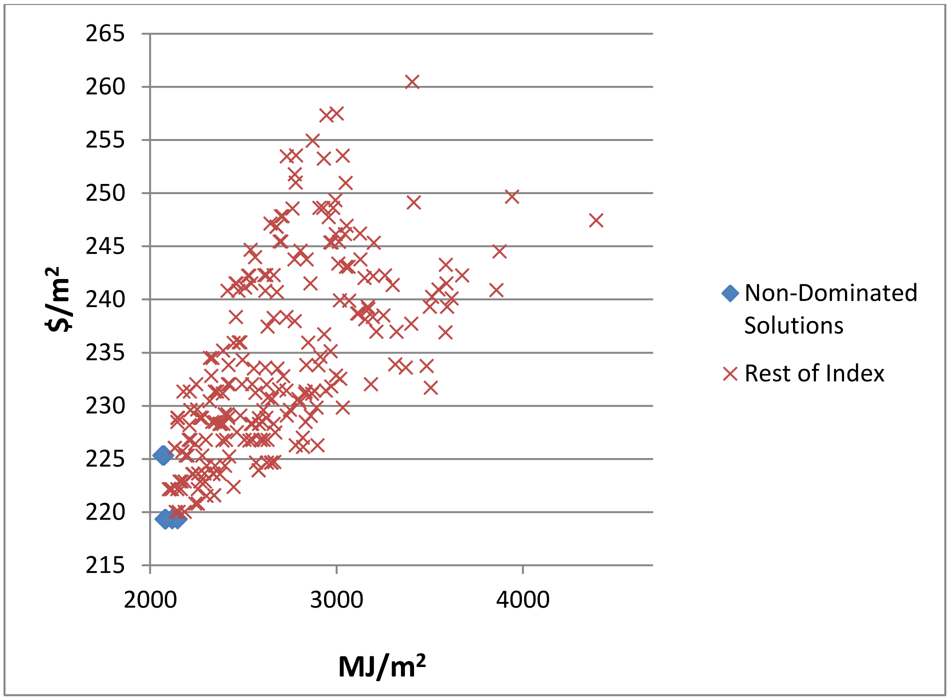

Figure 4.17. Trial 3 Pareto-optimal Curve of External Index

4.3. Analysis of Results

In general, Trial 3 performed as well and in the same manner as Trials 2A and 2B. All trials had search spaces in the same range and with the same properties.

The most striking find can be seen in Figure 4.18, which compares the first generation non-dominated solutions of Trials 2A, 2B, and 3. The population of Trial 3 clearly outperformed that of the other two trials. This makes for a clear case that the initial population was in fact partially optimized for Trial 3, as it contained both a larger amount of Pareto-optimal solutions and had better fitness values for those solutions.

Not only did Trial 3 start out with a better population set, it achieved the perceived optimal faster than the other two trials. Although the true global optimal is not known in this research for lack of a "brute force" testing method, this study will use the term "perceived optimal" for the solution with the best all-around fitness value as found from the three combined trials.

Trial 3 came across the perceived optimal solutions after only its third generation, as opposed to Trial 2B which found that solution after the fourth generation. As mentioned earlier, Trial 2A never converged on the perceived optimal after 5 generations.

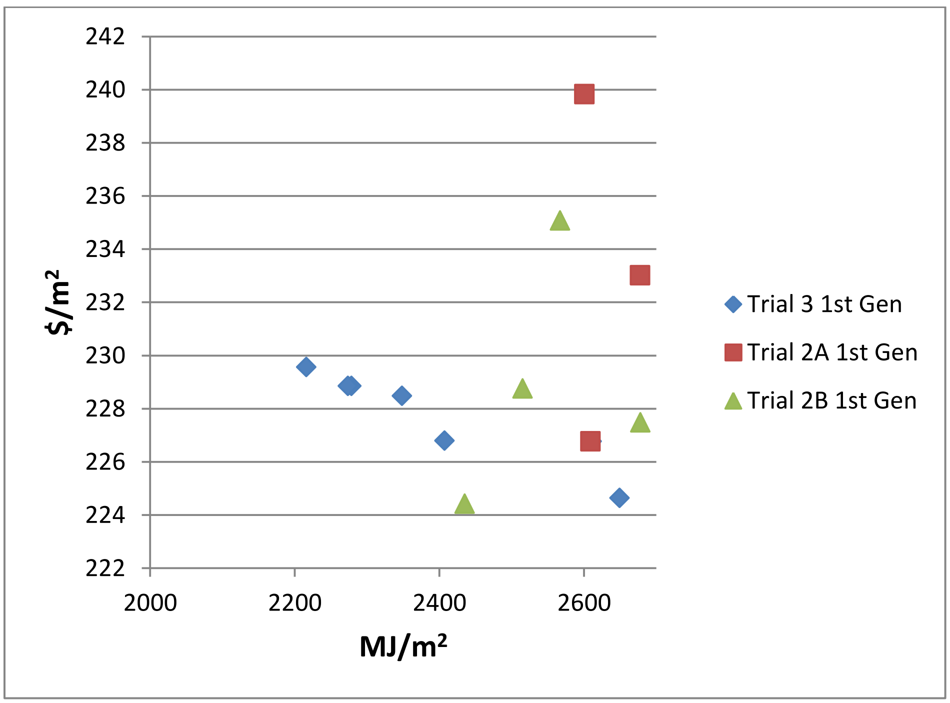

Figure 4.18. Comparison of First Generation Non-Dominated Solutions

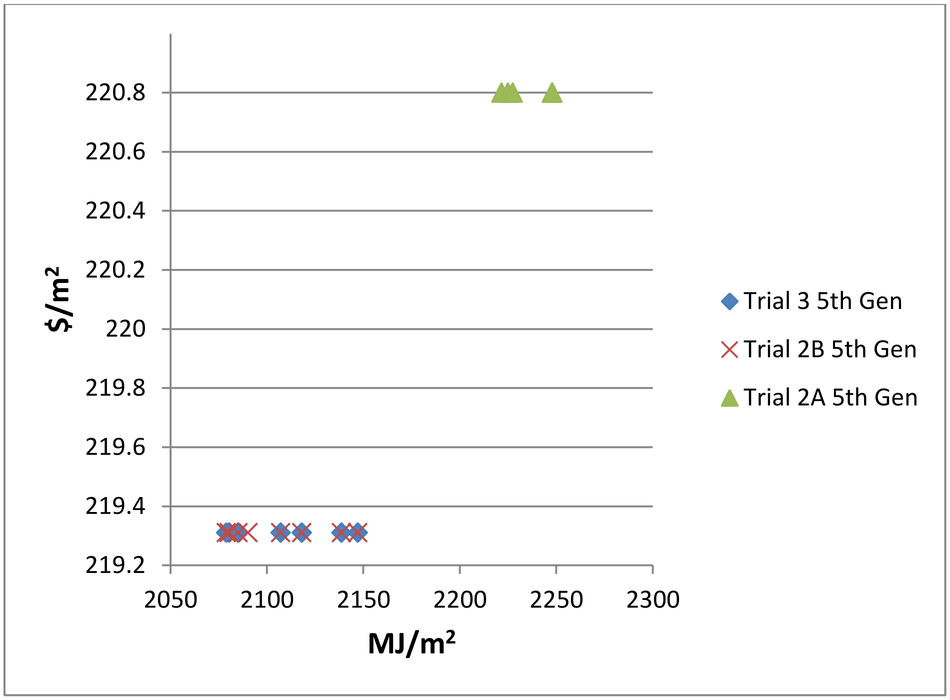

Figure 4.19. Comparison of Final Generation Non-Dominated Solutions

The final graphs show a comparison of indexed solutions across the trials. Figure 4.20 shows that from all of the solutions, Trial 3 did in fact have the most optimal combined with most varied fitness values when compared to the Trials 2A & 2B.

Figure 4.21 shows the non-dominated solutions from the indices of all four trials and is shown to demonstrate the potential of comparing cumulative trials. It stands to reason that the double glazing simulations of Trials 2A, 2B, and 3 will all be more expensive and use less energy than that of Trial 1 where single glazing is tested. Obviously, this is reflecting the fact that the double glazing is both more costly per area and has better thermal properties than single glazing.

In addition, Trial 1 shows a wide range of fitness goals in terms of both cost and performance. Trials 2A, 2B, and 3 are relatively narrow in solution range when compared to Trial 1. This result also is not surprising when considering the glazing properties. The double glazing cost is a closer match to the non-glazed portion of the building, making the cost not as variable depending on how much glazing there is on the building. The same concept holds true for the thermal properties. The double glazing is more comparable to the spandrel system, and therefore less energy swings can be recorded depending on how much or how little glazing is installed.

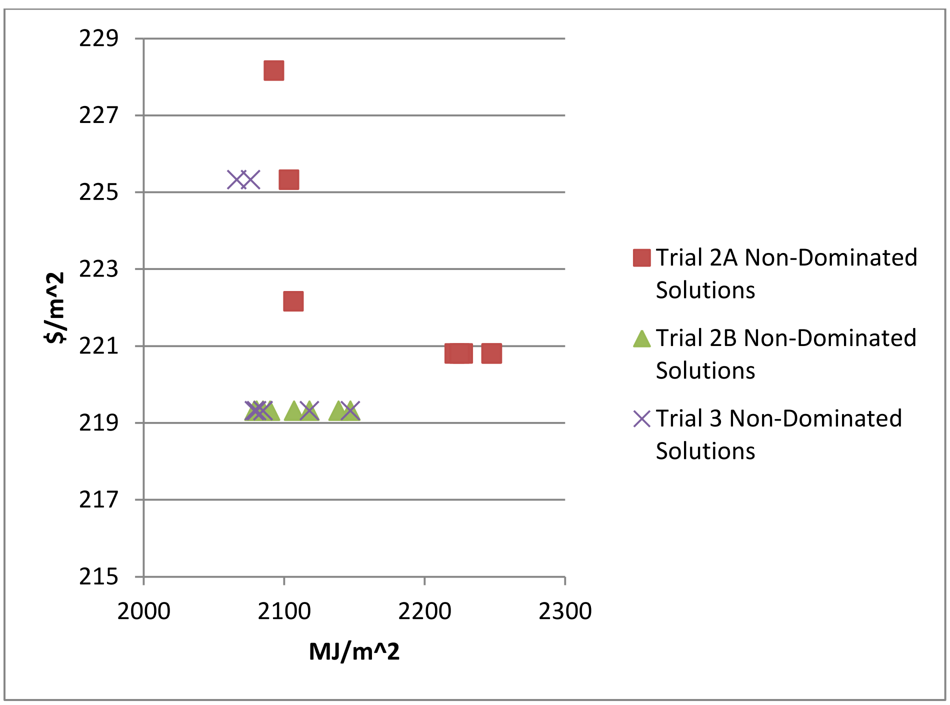

Figure 4.20. Trials 2A, 2B, and 3 Simulation Index Non-Dominated Solutions

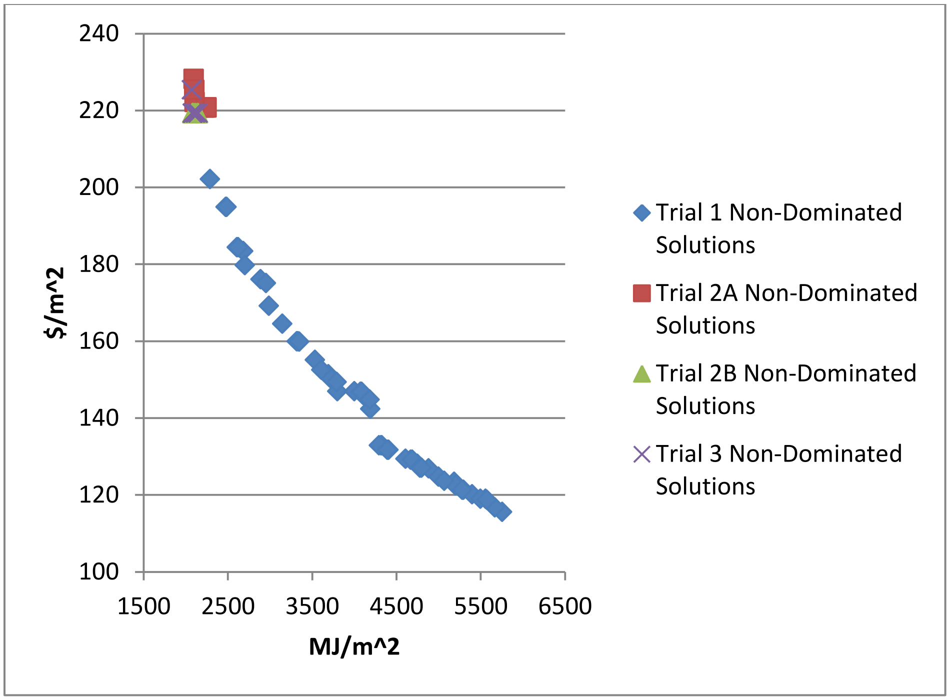

Figure 4.21. Non-Dominated Solutions from All Trials Index

CHAPTER 5: CONCLUSIONS

This study concludes that the proposed approach of seeding an initial population for a genetic algorithm with non-exact but similar previous studies can potentially improve results and reduce the computation time. The hypothesis stated in this research was not found null, and therefore not disproved. Ultimately, much more study is needed to conclusively demonstrate the complete validity of this proposed process, but these preliminary results are promising.

Hopefully, other research combining energy simulation indexing with partially optimized seeding will continue. The next steps would be to create a robust catalog of previous computations that will inform and seed future analyses. Eventually this process could be efficient enough to be applied in real-world applications and keep pace with real-time projects. In addition, this process has potential to reduce computational costs and time to a manageable level that is accessible to typical owners, contractors, and architects.

In the end, this process, or a similar method, has the potential to truly reduce building energy consumption and increase energy efficiency through dynamic energy modeling.

APPENDIX A

Energy Simulation Output Data Formatting

Table A.1. Integer Variable Keys

Integer	Building Orientation (degrees from N)	Percent Glazing (percent)
0	0	1
1	5	10
2	10	20
3	15	30
4	20	40
5	25	50
6	30	60
7	35	70
8	40	80
9	45	90

Table A.2. Simulation Job Prefix Key

Trial	Generation	Simulation Job Prefix	Trial	Generation	Simulation Job Prefix
Trial 1	Gen 1	A	Trial 2B	Gen 1	K
	Gen 2	B		Gen 2	L
	Gen 3	C		Gen 3	M
	Gen 4	D		Gen 4	N
	Gen 5	E		Gen 5	O
Trail 2A	Gen 1	F	Trial 3	Gen 1	P
	Gen 2	G		Gen 2	Q
	Gen 3	H		Gen 3	R
	Gen 4	I		Gen 4	S
	Gen 5	J		Gen 5	T

APPENDIX B

Results from Trials

Note: The following tables show non-dominated solutions from the external index for each trial. All solutions from every generation are compiled and given a Pareto rank as compared to the entire index, and all generations had a population of 100 solutions. Duplicate solutions in the following tables were removed for clarity.

Table B.1. Trial 1 Non-Dominated Results

Simulation Job #	Total Source Energy Use Output (MJ/m^2)	Construction Cost Output ($/m^2)	Integer Variable Building Orientation	Integer Variable Percent Glazing South	Integer Variable Percent Glazing East	Integer Variable Percent Glazing North	Integer Variable Percent Glazing West	Pareto Rank
A55	4668.52	129.11	0	9	5	8	0	1
B37	2606.3	184.42	1	1	1	6	0	1
B60	4609.16	129.36	1	9	4	9	0	1
B76	5295.81	121.34	1	9	4	9	7	1
B8	3534.08	155.13	0	4	2	9	0	1
B82	2287.44	202.13	0	1	1	2	1	1
B9	5397.34	120.18	0	9	6	9	6	1
B97	4750.29	128.07	0	9	5	8	1	1
C17	5184.3	123.42	0	9	5	8	5	1
C21	3712.87	150.44	1	5	2	9	0	1
C36	4688.28	129.11	1	9	5	8	0	1
C42	2684.71	183.38	1	1	1	6	1	1
C54	2887.06	176.09	1	3	0	6	0	1
C57	5756.65	115.53	1	9	7	9	9	1
C59	4191.68	142.38	1	6	1	9	4	1
C85	4072.19	146.82	1	5	5	8	1	1
C86	3334.27	159.93	0	3	1	9	1	1
C93	2473.12	194.85	0	3	0	2	0	1
D100	2703.93	179.74	1	1	1	7	0	1
D12	2624.08	184.42	0	1	1	6	0	1
D23	4408.07	131.69	1	9	2	9	0	1
D27	5556.28	119	0	9	5	8	8	1
D31	5667.77	116.7	1	9	6	9	9	1
D32	3798.08	146.91	1	6	1	9	0	1
D39	4001.49	146.91	0	9	1	6	0	1
D41	4327.72	132.85	1	9	0	9	1	1
D44	3695.13	151.35	1	5	2	8	0	1
D63	4076.16	146.82	0	5	5	8	1	1
D71	4315.82	132.85	0	9	0	9	1	1
D79	3316.04	159.93	1	3	1	9	1	1
D8	4106.45	145.91	1	5	2	9	4	1
D91	3348.75	159.82	0	3	2	9	0	1
D97	2485.36	194.85	1	3	0	2	0	1
D98	4998.05	124.69	0	9	8	8	0	1
E1	5496.56	119.02	0	9	6	9	7	1
E17	5202.34	122.51	0	9	5	9	5	1
E21	3715.62	150.44	0	5	2	9	0	1
E22	4883.42	126.9	0	9	3	8	4	1
E24	4295.28	132.85	0	9	1	9	0	1
E26	3145.74	164.51	1	2	2	9	0	1
E28	4088.8	146.82	1	5	2	8	4	1
E32	4390.41	131.69	0	9	2	9	0	1
E35	3611.61	152.51	1	5	0	8	1	1
E44	4779.71	127.04	0	9	6	9	0	1
E48	5069.63	123.67	1	9	7	9	2	1
E49	5573.94	118.77	0	9	5	8	9	1
E6	4799.36	127.04	1	9	6	9	0	1
E61	2987.58	169.2	1	1	2	9	0	1
E64	5280.69	121.34	1	9	7	9	4	1
E70	4183.5	144.75	1	5	6	9	1	1
E79	3791.13	149.39	1	5	2	9	1	1
E90	2953.4	175.05	1	3	1	6	0	1

Table B.2. Trial 2A Non-Dominated Results

Simulation Job #	Total Source Energy Use Output (MJ/m^2)	Construction Cost Output ($/m^2)	Integer Variable Building Orientation	Integer Variable Percent Glazing South	Integer Variable Percent Glazing East	Integer Variable Percent Glazing North	Integer Variable Percent Glazing West	Pareto Rank
H10	2227.42	221	3	0	2	0	0	1
I14	2221.64	221	1	0	2	0	0	1
I15	2224.93	221	2	0	2	0	0	1
I16	2092.85	228	1	1	0	2	0	1
I46	2248.09	221	8	0	2	0	0	1
I71	2247.93	221	9	0	2	0	0	1
J42	2106.7	222	1	2	3	2	0	1
J52	2103.56	225	1	1	0	3	0	1

Table B.3. Trial 2B Non-Dominated Results

Simulation Job #	Total Source Energy Use Output (MJ/m^2)	Construction Cost Output ($/m^2)	Integer Variable Building Orientation	Integer Variable Percent Glazing South	Integer Variable Percent Glazing East	Integer Variable Percent Glazing North	Integer Variable Percent Glazing West	Pareto Rank
M38	2147.27	219.31	9	0	0	0	0	1
N11	2118.18	219.31	6	0	0	0	0	1
N34	2085.18	219.31	2	0	0	0	0	1
N4	2080.5	219.31	1	0	0	0	0	1
N71	2078.98	219.31	0	0	0	0	0	1
O46	2107.18	219.31	5	0	0	0	0	1
O71	2138.8	219.31	8	0	0	0	0	1
O81	2090.22	219.31	3	0	0	0	0	1

Table B.4. Trial 3 Non-Dominated Results

Simulation Job #	Total Source Energy Use Output (MJ/m^2)	Construction Cost Output ($/m^2)	Integer Variable Building Orientation	Integer Variable Percent Glazing South	Integer Variable Percent Glazing East	Integer Variable Percent Glazing North	Integer Variable Percent Glazing West	Pareto Rank
Q49	2118.18	219.31	6	0	0	0	0	1
Q71	2085.18	219.31	2	0	0	0	0	1
R20	2147.27	219.31	9	0	0	0	0	1
R36	2078.98	219.31	0	0	0	0	0	1
R6	2076.25	225.32	2	0	0	2	0	1
R76	2080.5	219.31	1	0	0	0	0	1
S10	2085.18	219.31	2	0	0	0	0	1
S16	2066.47	225.32	1	0	0	2	0	1

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