ENHANCED SEQUENTIAL SEARCH STRATEGIES FOR IDENTIFYING COST-OPTIMAL BUILDING DESIGNS ON THE PATH TO ZERO NET ENERGY

by

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Enhanced Sequential Search Strategies for Identifying Cost-Optimal Building Designs on the Path to Zero Net Energy

Thesis directed by Associate Professor Michael J. Brandemuehl

Identifying cost-optimal building designs, particularly on the path to zero net energy, requires accounting for complex energy interactions between building measures. *BE*opt, building optimization software developed by the National Renewable Energy Laboratory, incorporates such interactions as it probes a large, multivariate parameter search space for optimal combinations of measures. Measures include wall constructions, window glazing properties, heating, ventilation, and air conditioning (HVAC) equipment, lighting, solar thermal, and photovoltaics.

*BE*opt utilizes a sequential search optimization methodology. Enhancements to this methodology, both in terms of robustness (ability to generate the true cost-optimal curve) and efficiency (number of required simulations), were developed and tested.

Regarding robustness, three deficiencies in the sequential search were investigated: the “invest/divest”, “large-step”, and “positive interactions” special cases. Solutions to the first two special cases do not require user interaction and were implemented in *BE*opt. Using a test suite (comprised of small, medium, and large optimizations across six climates), the occurrence of the two special cases were identified. The optimization results were additionally validated against large, but not exhaustive, parametric runs.

For search efficiency, eleven strategies were devised to reduce the total number of required simulations. The strategies work by either reducing the number of search iterations or by reducing the number of simulations per iteration. Five such strategies were found to be particularly effective without significantly compromising robustness: 1) skip predicted outliers, 2) skip fine points, 3) option lumping, 4) skip less efficient options, and 5) skip extraneous points. Combinations of these strategies were then assembled into efficiency packages, ranging from conservative to aggressive. The most conservative package achieves a 15% reduction in simulations (without any sacrifice on robustness), while the most aggressive package achieves a 71% reduction in simulations (with a 1.2% maximum deviation, compared to the reference optimization, in the cashflow of any optimal building design over the entire range of designs on the path to zero net energy).

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I. INTRODUCTION

In recent years, the personal computer has seen rapid advancements in processor speed. Before these technological improvements, building energy modelers were largely constrained by computer speed – thus, computer-modeling tools required much forethought on the user's part so that the number of building simulations could be kept to a minimum. Today, the user has much more freedom. Technological progress allows a user to run large numbers of simulations and have the computer optimize for a solution, eliminating much of the need for (potentially erroneous) prejudgment. The process has become less time-intensive and the results more accurate.

The building energy field has seen active development in software optimization tools in recent years, such as the National Renewable Energy Laboratory's *BE*opt. These tools employ a number of search methodologies in order to identify economic and energy-efficient building designs from the universe of possibilities. By providing optimal designs to anyone with a personal computer, researchers, planners, and end users can adopt building practices to stem the use of fossil fuels in a time of increased fuel costs and heightened awareness about pollution, health, and climate change.

II. OBJECTIVES

- Develop enhanced, supplemental strategies for the sequential search optimization methodology, in order to more efficiently and robustly identify cost-optimal building designs at various levels of energy savings along the path to zero net energy.

- Construct packages of efficiency strategies, ranging from conservative to aggressive, for potential implementation in the Building Energy Optimization (*BE*opt) software.

III. BACKGROUND

3.1 Zero Net Energy

Zero net energy (ZNE) buildings produce as much energy as they consume on-site annually. ZNE buildings employ grid-tied, net-metered photovoltaic (PV) systems and effectively use the grid as "battery storage" to reduce required PV capacity. These buildings typically include aggressive energy efficiency measures and active solar water heating systems.

3.1.1 Source vs. Site Energy

Zero net energy can be defined in terms of site energy (energy produced and consumed at the building site) and source (primary) energy. Source energy includes site energy plus the energy used to generate, transmit, and distribute this energy (1). Source energy quantifies the impact of fuel consumption to society and is better suited for zero net energy building analysis. It effectively allows different fuels, such as electricity and natural gas in the case of buildings, to be aggregated together.

3.2 Building Optimization

Building energy optimization entails adjusting various building components until a design is identified that achieves minimum cost and/or maximum energy savings. While exhaustive enumeration can be performed, in which every possible combination of efficiency measures in the search space is evaluated, optimization methods are often employed to minimize the number of combinations evaluated while hopefully still finding the same solution.

3.2.1 Multivariate Methodologies

Inherently, building design problems are multivariate; the parameter search space includes envelope insulation, HVAC (heating, ventilation, and air conditioning), equipment, appliances, lighting, water heating, geometry and form, renewable generation, and so on. Multivariate optimization problems are more complex than univariate problems.

Various techniques exist to perform multivariate optimization. Multivariate optimization techniques are typically grouped into three categories: Zero-order methods, which require only function values to make a decision, first-order methods, which utilize gradient information and are generally more efficient than zero-order methods, and second-order methods, which make use of both the current slope of the function as well as its rate of change.

3.2.2 Discrete Versus Continuous Variables

Multivariate optimization can be performed either within the continuous or discrete world. Typical building optimization, such as those methods employed by GenOpt (2), falls within the continuous realm. Such optimization strategies include the coordinate search algorithm (3), pattern search algorithm of Hooke and Jeeves (4), multidirectional search algorithm of Dennis and Torczon (5), and the Simplex algorithm from Nelder and Mead, including improvements to prevent deficiencies in finding the optimal point (6). The aforementioned optimization strategies are all examples of Generalized Pattern Search (GPS).

When variables in the search space are instead restricted to finite sets of values, the variables are referred to as discrete variables. Two types of discrete variables are pseudo-discrete variables, those that physically can be continuous but are restricted by extraneous information, and integer variables, those for which there is no meaningful interpretation of a non-integer value (7).

When designing real buildings, discrete building parameters are of particular interest to us. These parameters typically consist of both pseudo-discrete and integer variables. Window area, an example pseudo-discrete variable, is theoretically continuous but restricted only by the specific manufactured window sizes, while the number of floors in a building must be integer. Optimization problems for which the set of possible solutions is discrete, and which strive to identify the single best set of parameters, fall under the realm of combinatorial optimization.

Aside form rudimentary discrete optimization techniques like exhaustive enumeration and Monte Carlo (random), Genetic Algorithms (GA) are most commonly used for building energy optimizations that make use of hourly annual simulations (8). GA has been used in building energy applications by Wright and Loosemore (9) and Caldas and Norford (10). Other discrete optimization algorithms include Simulated Annealing and TABU.

3.2.3 Constrained Optimization

Optimization is typically concerned with identifying the single, global optimum – the building design that minimizes cost. If this objective function is to be minimized without additional constraints, the optimization will find the global minimum illustrated by point A in Figure 1. However, when constraints are involved in the optimization process, results shown by points 1 and 2 are obtained; these points represent cost-minimum buildings at 10% and 20% target energy savings levels, respectively. Constraints are generally performed to incorporate ancillary information, economic or otherwise, not covered by the objective function.

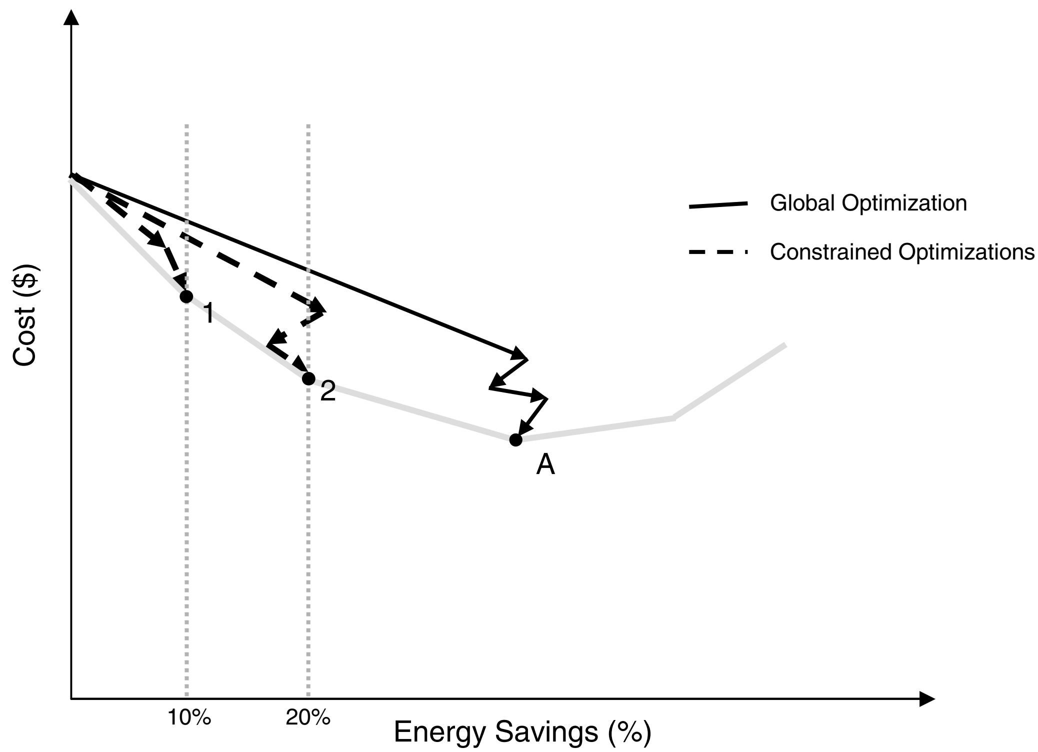

Figure 1: Global (Unconstrained) vs. Constrained Optimization

3.2.4 Near-Optimal Solutions

Often it is desirable to identify both optimal and near-optimal solutions in order to provide alternative building designs. These near-optimal solutions achieve energy savings and costs nearly identical to the optimal point and, given the uncertainty in modeling and cost assumptions, should be considered essentially equivalent results to the optimal solution. Optimization strategies that provide these near-optimal solutions have an added benefit for building design analysis.

Moreover, being able to provide a certain level of diversity, in terms of building measures available in the near-optimal solutions, among the near-optimal building designs is also a plus. Such diversity can be accomplished by maximizing the number of energy measures in the parameter search space that show up in the optimization results. Diverse near-optimal solutions provide additional flexibility to the end user.

Finally, optimization techniques that provide additional solutions near the optimal boundary of the search space increase the likelihood of solutions available at any given target level. In contrast, many classic optimization strategies involve taking large steps in order to quickly get in the region near the global optimum; these strategies introduce gaps along the lower boundary of the search space. For purposes of identifying cost-optimal building designs along the path to ZNE, these gaps are undesirable and should be avoided, if possible.

3.3 Building Energy Optimization Tools

A number of optimization tools and/or methodologies exist to identify energy-efficient building designs at minimum cost.

3.3.1 ACT²

Davis Energy Group (DEG), an energy consulting firm based in California, developed a spreadsheet-based “sequential analysis process” for Pacific Gas and Electric’s Advanced Customer Technology Test for Maximum Energy Efficiency (ACT²) project (11, 12). Performance evaluations of energy efficiency measures (EEM's) in the presence of a base case building model are obtained via simulation. Cost evaluations for each measure are also calculated. Measures are ranked by their benefit cost ratios (BCR's) and the next most cost-effective EEM is introduced into the efficiency design package.

Upon the selection of each measure, energy performance results require updating due to interactions. Because some EEM's, like water heating, act relatively independent of space-conditioning, their sequential rankings were pre-computed. Additionally, time constraints prevented full analysis of every EEM at each step so only the three to seven most cost-effective measures, based on user judgment, were reanalyzed. The analysis continued until all EEM's with incremental BCR's greater than 0.5 or 0.7 were selected for the design package.

3.3.2 GenOpt

Developed at Lawrence Berkeley National Lab, GenOpt is a generic optimization program that hooks into external simulation engines in order to minimize a cost function. It includes a number of optimization methodologies, including coordinate search, pattern search, simplex, and, more recently, the swarm method. Variables can be continuous, discrete, or both, and can include penalty or barrier functions. Minimization algorithms can also be developed by the user.

3.3.3 Zero Net Energy Optimization Based on Marginal Costs

In 2002, NREL devised an optimization approach to determine the minimum-cost zero net energy building (13). The approach strives to find the single efficiency measure within each category whose marginal cost of saved energy is closest to, but less than, the cost of producing electricity from PV. The ZNE building design solution includes this set of options coupled with enough PV capacity to reach zero net energy.

3.3.4 Energy Gauge Pro

Energy Gauge Pro (14), developed by the Florida Solar Energy Center (FSEC), incorporates an economic analysis feature called Successive, Incremental Optimization. The optimization process provides a recommended energy-efficiency upgrade package to the user based on the specified Energy Savings Goal, financial Ranking Method, first cost limit, and so on. The best energy efficiency measures are chosen from a user-selectable table of EEM's (either custom or software defaults). Energy costs, cost-benefit analysis, cash flow schedules, and other parameters of the improved house are compared against the reference. Energy Gauge Pro only performs optimization for Florida climates and should not be confused with the more well-known Energy Gauge USA (15), which can perform simulation for locations across the country but does not involve optimization.

3.3.5 BEopt

*BE*opt (16), the Building Energy Optimization tool developed by the National Renewable Energy Laboratory, is a computer program designed to identify cost-optimal building designs at a variety of energy savings levels, typically from a reference building (e.g. user-defined or Building America Benchmark (17)) to zero net energy (ZNE). The range of building design options available for optimization is chosen from predefined or custom efficiency and renewable energy measures. Energy savings for each measure are calculated compared to a reference building on a source energy basis. Costs for building measures are generally derived from RS Means (18) or manufacturer's data, or they can be user-specified.

*BE*opt calls the DOE-2 (19) and TRNSYS (20) simulation engines to automate the process of finding optimal building designs. DOE-2 is used to calculate building loads and simulate HVAC equipment, while TRNSYS is used for simulating hot water usage and PV. *BE*opt uses .bmi files (*BE*opt Macro Input files) to construct valid simulation engine input files. The .bmi files are a mix of skeletal simulation engine language (e.g. BDL for DOE-2) and *BE*opt Macro Language, which is a rudimentary scripting language allowing for calculations, variable assignments, arrays, looping, etc. The *BE*opt Macro Language is loosely modeled after DOE-2's macro language; however, it has removed some limitations, added functionality, and can work with any simulation engine. The .bmi files are processed through a *BE*opt Macro Interpreter executable that generates the actual DOE-2 and TRNSYS input files needed for a specific building design.

The current listing of categories of efficiency measures available for optimization are: orientation, neighbors, misc. electric loads, heating set point, cooling set point, wall insulation, ceiling insulation, thermal mass, infiltration tightness, foundation insulation, window area and type, eaves, large appliances, lighting, HVAC equipment, water heater, ducts, solar DHW, and PV. In addition to these, *BE*opt allows the user to manipulate the geometry of the building in terms of floor area, aspect ratio, number of floors, type of garage, and type of roof. Economic inputs, such as electric and natural gas utility rates, mortgage interest rate, and net-metered excess electricity sellback rate, are also available to the user.

Results displayed on the BEopt output screen include the Cost/Energy graph, an End Uses breakout graph, and an Options graph that describes the building and the capital costs associated with its energy measures. Multiple simulated buildings can be quickly selected and compared against one another. Additionally, *BE*opt can export buildings into eQUEST (21) or SketchUp (22) for building rendering and DView (23) for visualizing hourly simulation output and statistical analysis.

A conceptual plot of the Cost/Energy graph from *BE*opt is illustrated in Figure 2. At the starting point of the optimization (point A), utility bills comprise the entirety of the building's energy-related cost as no efficiency upgrades have been included to cause an increase in mortgage. As efficiency measures are introduced into the building, incremental mortgage costs increase and utility bills decrease until the marginal cost of saved energy equals the cost of utility power. Here the curve reaches a minimum and the global cost-optimum point is reached (point B). Additional efficiency measures with marginal costs more expensive than the cost of fuel are introduced until the marginal cost of saved energy equals the marginal cost of producing PV energy (point C). At this point, PV capacity is added until all source energy use is offset (point D). In roof-constrained scenarios, where there is a limit to the number of PV panels that can fit on a building's roof, additional efficiency is employed after PV until zero net energy is reached. This additional efficiency has a marginal cost of saved energy greater than that of the produced energy from PV. If all efficiency measures in the optimization search space are exhausted before zero net energy is attained, the optimization stops at its maximum possible energy savings level.

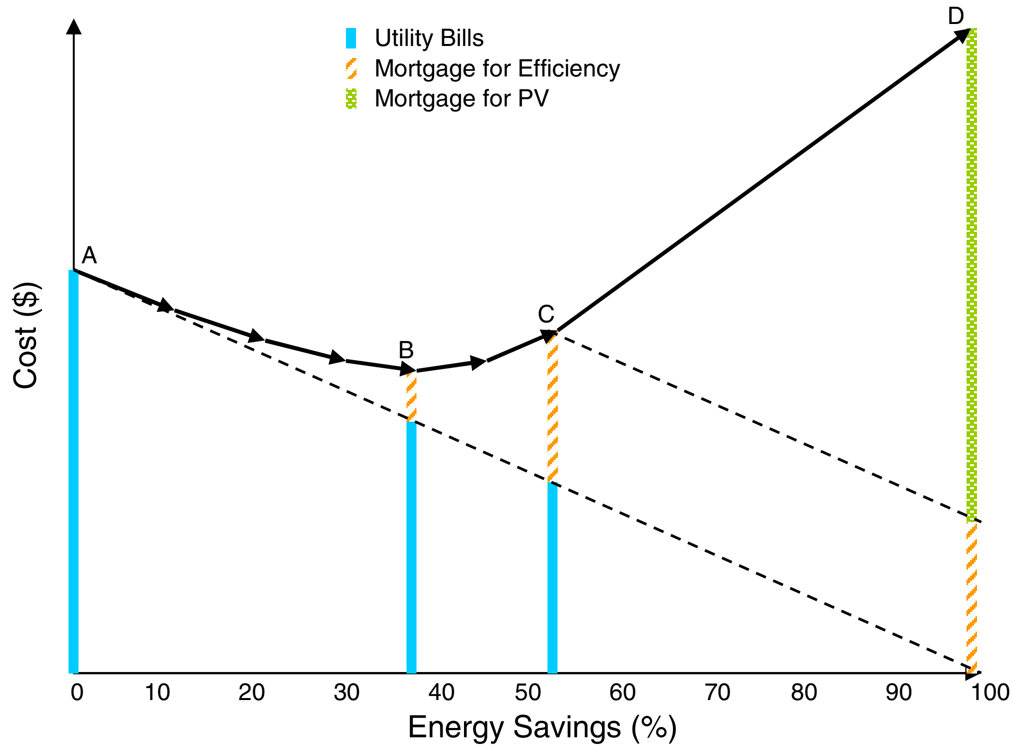

Figure 2: Conceptual Plot of Path to ZNE

One could consider using a series of constrained optimizations to generate the cost-optimal path above described for the Cost/Energy graph, but this is a rather inefficient process. *BE*opt instead employs a modified sequential search optimization strategy (24) developed from the ACT^2 methodology. The choice of search strategy was influenced by three goals:

1. Interest in intermediate optimal points (minimum cost designs at various levels of energy savings)
2. Discrete, realistic building descriptions, and
3. Identification of near-optimal alternative designs.

The basic sequential search process entails evaluating efficiency measures across categories (e.g. wall insulation, window glazing, HVAC equipment) to determine the most cost-effective option at each sequential point along the path to ZNE. These options are simulated one by one in the presence of an initial building design and, based on simulation results and energy-related costs, the most cost-effective option is chosen as the next optimal point. The chosen option is then removed from the parameter search space for future evaluation. Remaining efficiency measures are simulated in the presence of this new optimal point and the iterative process repeats (see Figure 3). Robustness modifications to the basic sequential search methodology, which are present in *BE*opt, are described in Chapter 4.

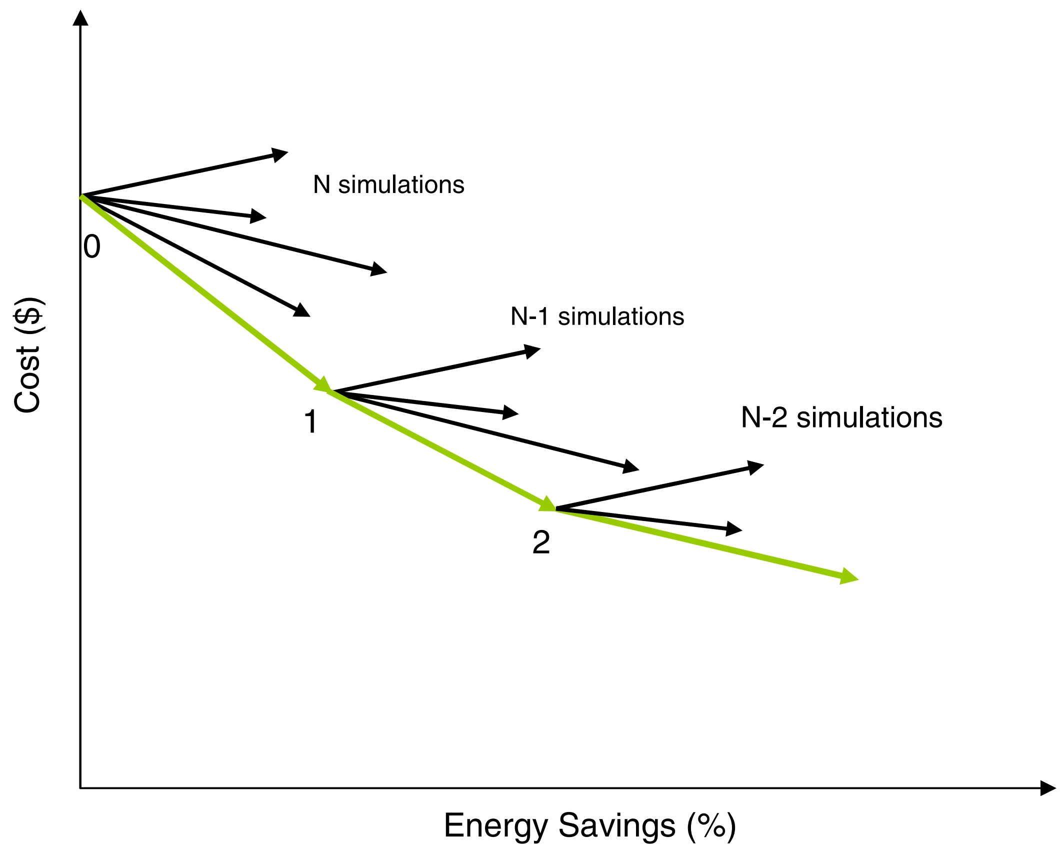

Figure 3: Basic Sequential Search Process

Upon the conclusion of each iteration's building simulations, the marginal cost of the most cost-effective efficiency measure is compared to the cost of photovoltaic (PV) energy. At the point where further improving the building has a higher marginal cost, PV is employed until zero net source energy is achieved, as illustrated in Figure 4. In the case of roof-constrained PV, additional efficiency measures are employed at the end of the PV segment until either zero net energy or maximum energy savings is achieved.

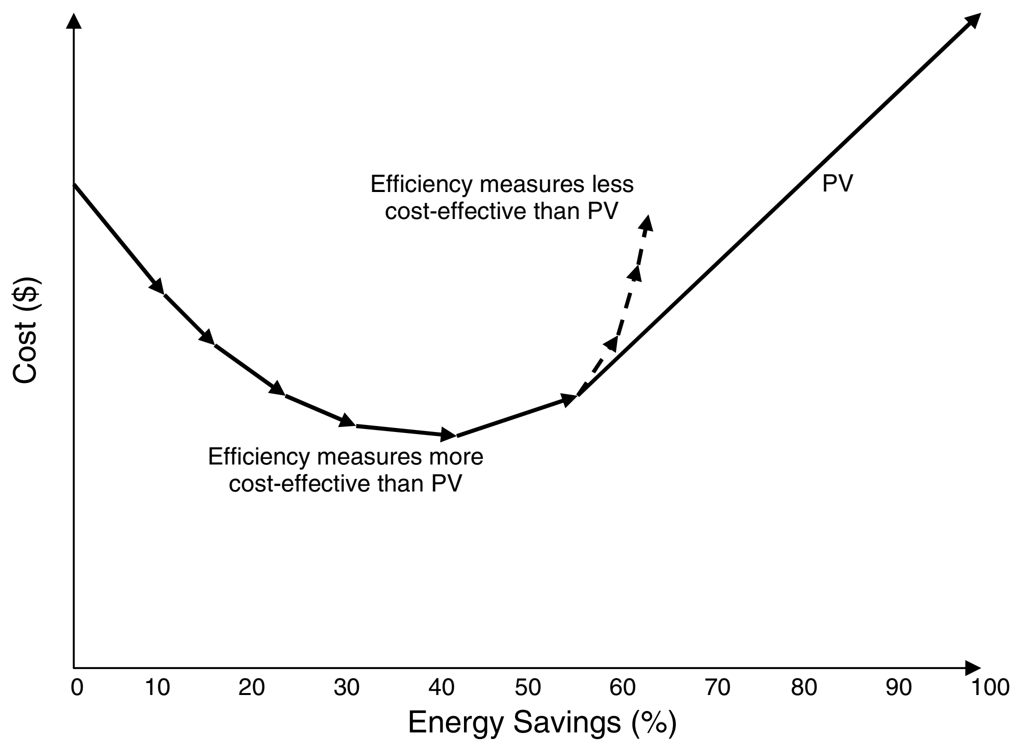

Figure 4: Path to ZNE, Sequential Search

The optimization process that currently exists in *BE*opt version 0.8 is considered modified from the basic sequential search methodology because it incorporates the "special case" robustness strategies that will be detailed in Chapter 4 as well as the Modularized Simulations efficiency strategy that will be discussed in Chapter 5.

The sequential search process is well suited for identifying a diverse set of alternative building designs at a given level of energy savings and energy-related cost. Despite not offering the number of alternative solutions than an exhaustive parametric strategy would obtain, each iteration of the sequential search produces a cloud of simulated building designs that does include every available building measure in the chosen parameter search space.

The sequential search methodology also minimizes gaps along the cost-minimum lower boundary of the cloud of points (see Figure 5). By searching building designs that differ by one efficiency measure from the previous optimal building design, avoidable gaps along the lower boundary of the cloud of points tend to be reduced. This helps ensure that there is a large possibility of cost-minimum building designs being in the vicinity of the user's target energy savings level.

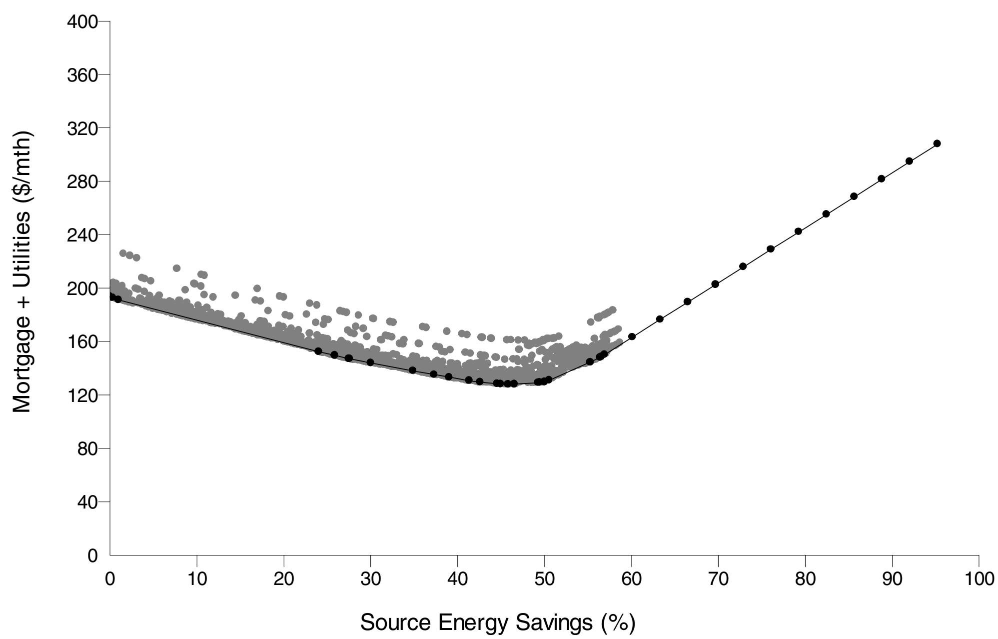

Figure 5: Typical Optimization Results from BEopt, Cost/Energy Graph

3.4 Benefits of Detailed Optimization

The goal of detailed optimization strategies, such as the sequential search methodology described above, is to find optimal building designs over a range of energy savings without resorting to exhaustive enumeration. One could consider simpler optimization strategies that attempt to identify a lower boundary path of building designs while requiring fewer simulations than the sequential search. By comparing detailed optimization against simpler optimization strategies (like those that might be manually employed by building energy modelers), the benefit of a detailed optimization approach can be observed.

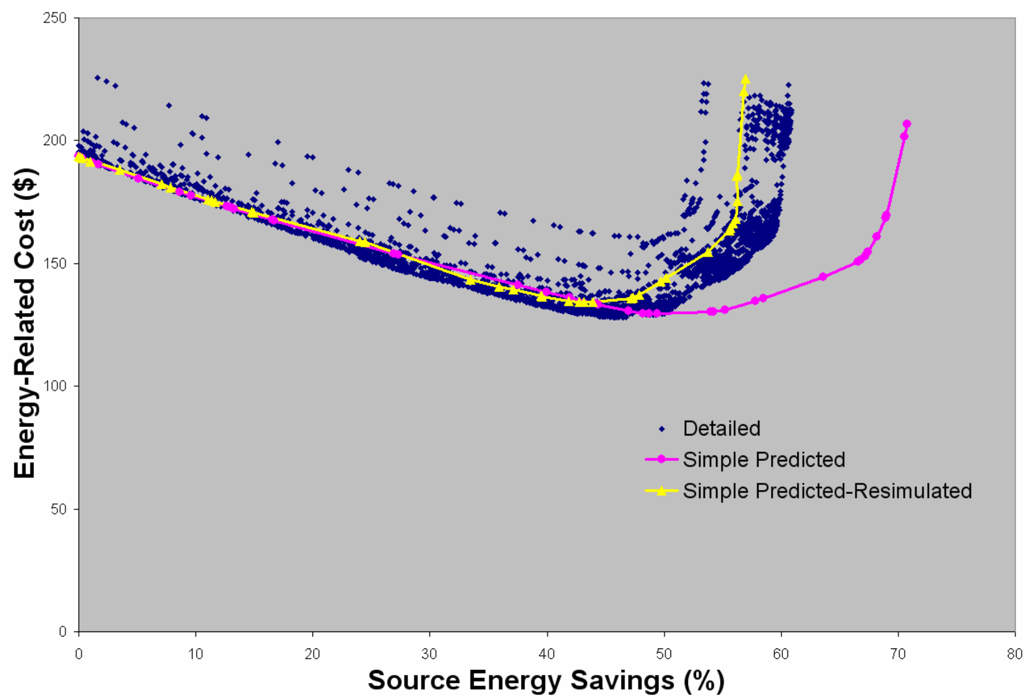

Figure 6: Comparison of Detailed and Simple Optimization Strategies

Suppose that a modeler, using an initial building design, runs a simulation for every energy efficiency measure one-at-a-time (equivalent to the first iteration of a sequential search). Then, within each category, the modeler iteratively finds the best ordering of options based on progressive slopes. In contrast to incremental slopes previously described for BEopt, where all options within an iteration have slopes calculated from a single reference point, progressive slopes are calculated using a series of reference points. So, for a particular category, the option that achieves the steepest slope is first selected, then this option is removed and the option that achieves the next steepest slope relative to the previous selected option is selected, and so on. The progressive process continues until all options within the category have been chosen relative to the previous selected point (see Section 5.1.7 for a more detailed explanation). Once ranked, costs and energy savings for options spanning all categories are sequentially strung together from steepest incremental slope to shallowest in order to form a lower boundary curve (shown in magenta, Figure 6). This curve is the predicted path that would result if there were no energy interactions. Because interactions do exist, this curve significantly over-predicts the potential energy savings.

The over-prediction of energy savings can be eliminated by adding a second step to the simple optimization process. Rather than mathematically adding together incremental energy savings and cost vectors for building simulation predictions, options are sequentially re-simulated in the presence of the other efficiency measures in order to obtain the path shown in yellow. By accounting for interactions in the building simulations, this path no longer over-predicts energy savings relative to the detailed optimization.

However, the re-simulated path fails to find optimal buildings at higher energy savings levels. This is caused by the use of the original rank ordering of options (whereas the sequential search method recalculates slopes after each efficiency measure is introduced into the building), resulting in the selection of suboptimal building designs. The re-simulated path, as well as the predicted path, also yields results above the lower boundary at lower energy savings due to these suboptimal building designs.

IV. ROBUSTNESS STRATEGIES

During initial development of *BE*opt, deficiencies in the basic sequential search method were identified. Strategies were devised in order to increase robustness of the search – that is, the optimization's ability to discover the lowest cost building designs over the range of energy savings levels.

4.1 Optimization Starting Point

The starting point of an optimization can affect its ability to discover the true cost-optimal path. The best approach defines the initial building design as the least efficient option in each category[1]. This increases the likelihood of identifying the cost-minimum path. (Another possibility involves choosing the lowest cost option in each category as a surrogate for inefficiency, but there is no guarantee that the lowest cost option consumes the most energy.)

[1] Some categories, like glazing type, are difficult or even impossible to order from least to greatest energy savings because of their dependency on climate or other building characteristics.

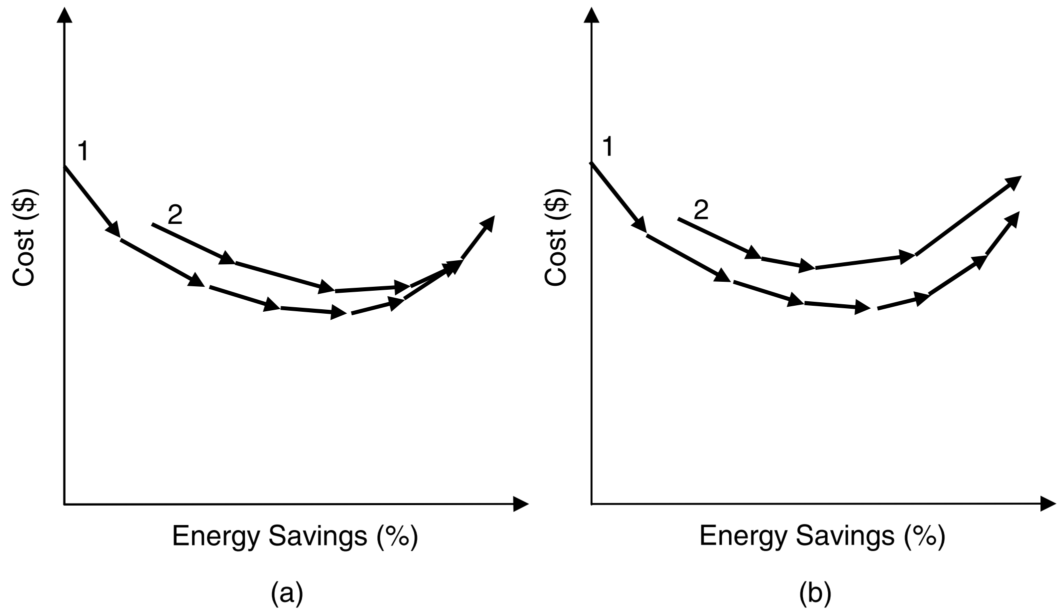

Figure 7: Effect of Starting Point on Optimization; (a) Converging Optimizations, (b) Non-Converging Optimizations

Figure 7 illustrates the reason for selecting an inefficient initial building design as the starting point. Path 1 represents the lower boundary of an optimization with the most inefficient initial building design possible and path 2 represents the lower boundary of an optimization where the initial building contains a number of efficiency improvements. Since each iteration of the basic sequential search results in a building design with a single efficiency measure change relative to the previous building, it may take many iterations before the two paths converge, as shown in Figure 7a. In fact, it is even possible that the two paths never do converge before the optimization reaches ZNE, as shown in Figure 7b. Whether or not convergence occurs, there may be a region of energy savings over which path 2 achieves suboptimal building designs relative to path 1 because of its more efficient starting point. Therefore, choosing an inefficient initial building design can improve the optimization's robustness at finding the cost-minimum building designs.

4.2 Special Cases

Three special cases have been discovered that represent deficiencies in the basic sequential search technique with respect to robustness. The situations are discussed below in detail along with strategies for improvement.

4.2.1 Large-Step (Strategy #1)

The large-step special case arises as a result of the basic sequential search looking for the next optimal point (or, the next steepest slope increment) within the set of points simulated *during the current iteration only*. In some circumstances, the next steepest slope point could actually come from a previous iteration.

For example, in Figure 8, the six vectors stemming from optimal point 0 represent a single iteration – six one-option changes from an optimization starting point. Because the sequential search strives for reducing energy use at minimum cost, it selects the point with the steepest slope (point 1) as the next optimal point whether or not it achieves the most energy savings of the points.

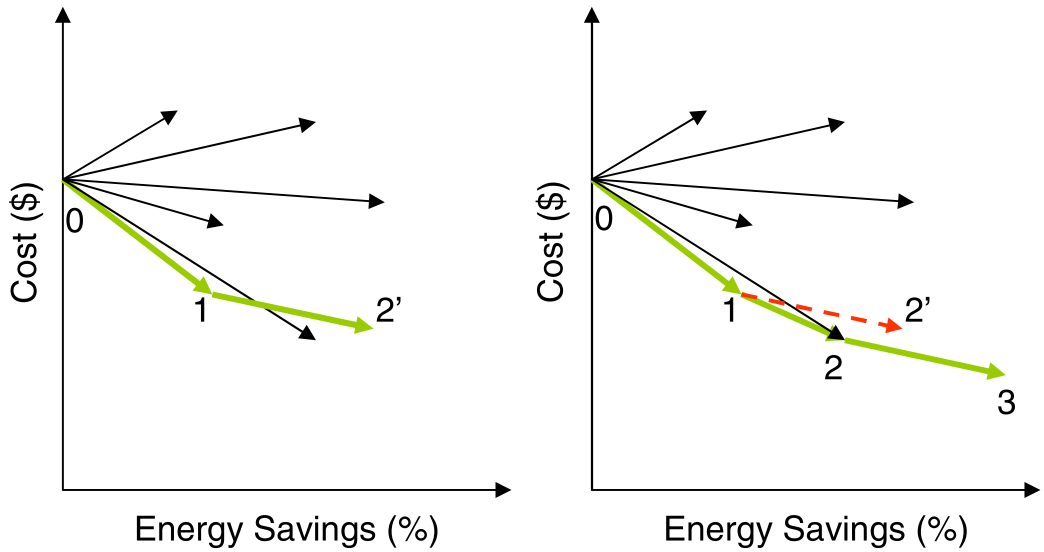

Figure 8: Large-Step Special Case

Next, upon simulating another full iteration of points, point 2' is the steepest slope *of the current iteration*. However, from visual inspection, we can see that point 2, a point simulated in the previous iteration, actually achieves a steeper slope from point 1. If the sequential search chose optimal points without evaluating all points of previous iterations in addition to the current iteration, points with better energy savings to cost ratios like point 2 would be neglected. Instead, the sequential search should evaluate all historical buildings simulated and choose point 2 as the next optimal point from which to proceed. Therefore, to accommodate the large-step special case, the modified sequential search retains information on every simulated point during the optimization process to help ensure the identification of the true cost-minimum path.

Unlike the following two special cases, this strategy improves the robustness of the search without a corresponding increase in simulation time; the strategy merely makes use of all known information. While a runtime penalty exists for having to search and revalidate the entire cost-optimal path at the conclusion of each iteration, the potential benefits to robustness warrant this small increase in computational effort.

4.2.2 Invest/Divest (Strategy #2)

The second special case involves the idea that you can invest aggressively in one sector of energy efficiency and subsequently divest in another because it proves less effective in the presence of this large investment. Hypothetically, suppose that the search chooses upgrading to a high SEER air conditioner in Phoenix early in the optimization process due to its cost effectiveness in the more inefficient buildings. As the optimization subsequently pushes towards zero-net energy, all of the various envelope-related efficiency measures employed could reduce the cooling to such a small load that the high efficiency air conditioner is no longer the cost-effective option it once was. The optimization could therefore divest in the high efficiency air conditioner and use this cost savings for more cost-effective measures.

The solution to the invest/divest special case involves "looking backwards" – that is, simulating efficiency measures even after they have been superseded by more efficient options. In the figure below, the sequential search simulates a series of buildings from optimal point 2, with their cost and energy savings impacts denoted by the vectors. If the sequential search only evaluates efficiency options that have not yet been chosen, the vectors that protrude to the right and achieve positive energy savings would be evaluated and the steepest slope of these points would be chosen for the next optimal point. However, by looking backwards and simulating efficiency options that have already been superseded, the two line segments that protrude to the left would also be found – and, in this example, point 3 proves to be the next best point.

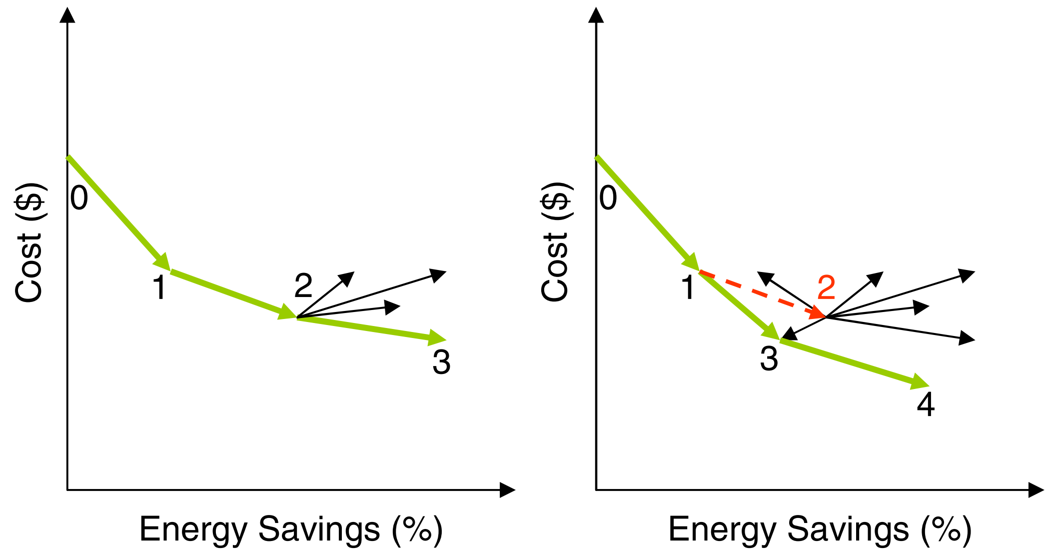

Figure 9: Invest/Divest Special Case

Because the sequential search aims to define the lowest boundary of the universe of simulated points, point 3 ought to be connected to optimal point 1 and not optimal point 2. Optimal point 2 is consequently removed from the lower boundary and is referred to as an "orphaned" optimal point. An orphaned point was an optimal point at one time but has subsequently been superseded by a better point and no longer falls along the cost-optimal path.

4.2.3 Positive Interaction (Strategy #3)

The previous special cases involved negative energy interactions; this final special case involves positive interactions. In the figure below, the sequential search simulates a series of options in the presence of optimal point 1, and point 2 is found to have the steepest slope. The subsequent iteration produces the vectors stemming from optimal point 2, and this time a slope is produced that is even steeper than the slope of the vector connecting points 1 and 2. Because this steep slope was not found in the previous iteration, this option must be positively interacting with the option introduced in optimal point 2 (i.e. producing greater energy savings in the presence of option 2 than in the presence of option 1).

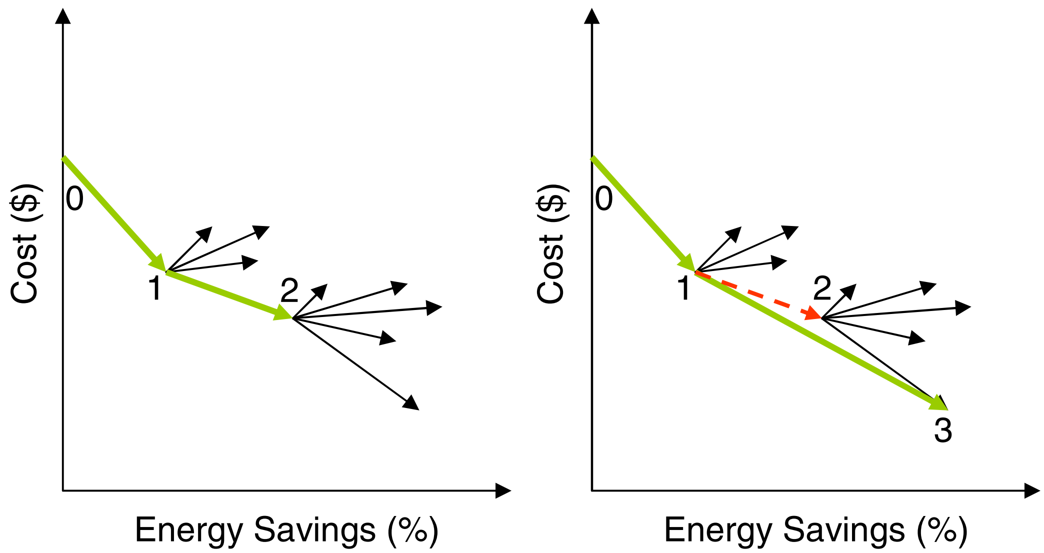

Figure 10: Positive Interaction Special Case

In order to provide the cost-minimum path, optimal point 2 ought to be orphaned and optimal point 3 should be directly connected to optimal point 1. Indeed, cases of positive interactions can be identified during the sequential search process.

Passive solar options illustrate a typical case. Suppose an optimization includes two window distribution options (equal distribution and increased south-facing window area) and two thermal mass options (no thermal mass and high thermal mass). The sequential search simulates buildings in the first iteration from the optimization starting point (equal distribution and no thermal mass). Because the sequential search evaluates options one at a time, the combination of increased south-facing window area and high thermal mass will only be simulated if either of the individual options first becomes cost-effective and is selected by the search.

The only way to automate a test for this positive interaction special case involves running a single iteration with all two-option combinations (in addition to the single options that are normally simulated). One could then determine if the energy savings for any two-option combination is greater than the sum of the two individual options' energy savings; if so, the combination includes positive interactions and would be evaluated in all subsequent iterations. The problem with this approach is one of runtime. The number of two-option combinations that need to be simulated are calculated by the following equation:

$$Simulations = \sum_{i=1}^{Nc-1}\left[(No-1)\cdot\sum_{j=i+1}^{Nc}(No-1)\right]$$

where Nc is the number of categories in the search space and No is the number of options within a given category. For an example optimization with 75 options selected across 20 categories, the number of simulations required is about 2,000, or roughly the same as the number of simulations across the entire optimization. This essentially doubles the runtime of an optimization. And trying to search for three-option combinations that yield positive interactions would further increase the runtime.

Because the penalty for searching for positive interaction special cases is prohibitively high, a manual approach is the only viable method. Allowing the user to explicitly specify combinations of options to be evaluated within each iteration would prevent these positive interactions from being overlooked. Although this approach requires a user to exercise his or her engineering judgment prior to running an optimization, it provides a flexible method for evaluating any potential positive interactions without causing a large increase in runtime.

4.3 Generalizing PV

As initially implemented, the basic sequential search methodology performs simulations for all efficiency measures in the search space, chooses the point relative to the previous optimal point with the steepest slope, and compares its marginal cost of saved energy to that of photovoltaics' electricity production. The inherent assumption is a linear relationship between PV size and output, and PV size and cost. While the former assumption is reasonable[2], the latter is not. This is due to non-linear capital costs and variable cost savings per unit of energy.

The non-linearity of capital costs reflects the realistic nature of purchasing photovoltaics for a residential building. Typically the capital cost of PV ($/rated watt) involves a number of factors, some of which may indeed vary linearly with system size (i.e. array cost) and some which may not (i.e. fixed labor charges). For this reason, PV usually includes economies of scales such that larger PV arrays are less expensive per watt than smaller arrays. Because the slope of PV (cost vs. size) is not necessarily linear, comparing the marginal cost of saved energy for efficiency against a linear cost of PV energy is suboptimal.

Variable cost savings per unit of energy, on the other hand, occur when an optimization has mixed fuels (e.g. electricity and natural gas). If we assume that PV first offsets electricity consumption, utility bills will initially decrease at the marginal electricity rate as the homeowner's monthly electric utility bills decrease. Once all electricity is offset, any additional PV output offsets natural gas consumption. Since net-metering typically occurs only on the electric side, this extra PV energy does not reduce

[2] One could imagine a situation where increasing PV array sizes results in more shading, for example, but this is quite unique.

natural gas bills; rather it involves selling excess produced electricity back to the electric utility. If the excess electric sellback rate is equal to the marginal electricity rate, then the cost curve continues to decrease at the same marginal electricity rate slope. But if the excess electric sellback rate is less than the marginal retail rate of electricity, the homeowner would see a reduced cost savings per unit of source energy saved. The end result is a PV line made up of two distinct slopes – the slope at the marginal electricity rate, which proceeds until building electricity use is completely offset, and the slope at the excess sellback rate that is used to offset natural gas consumption, as shown in Figure 11.

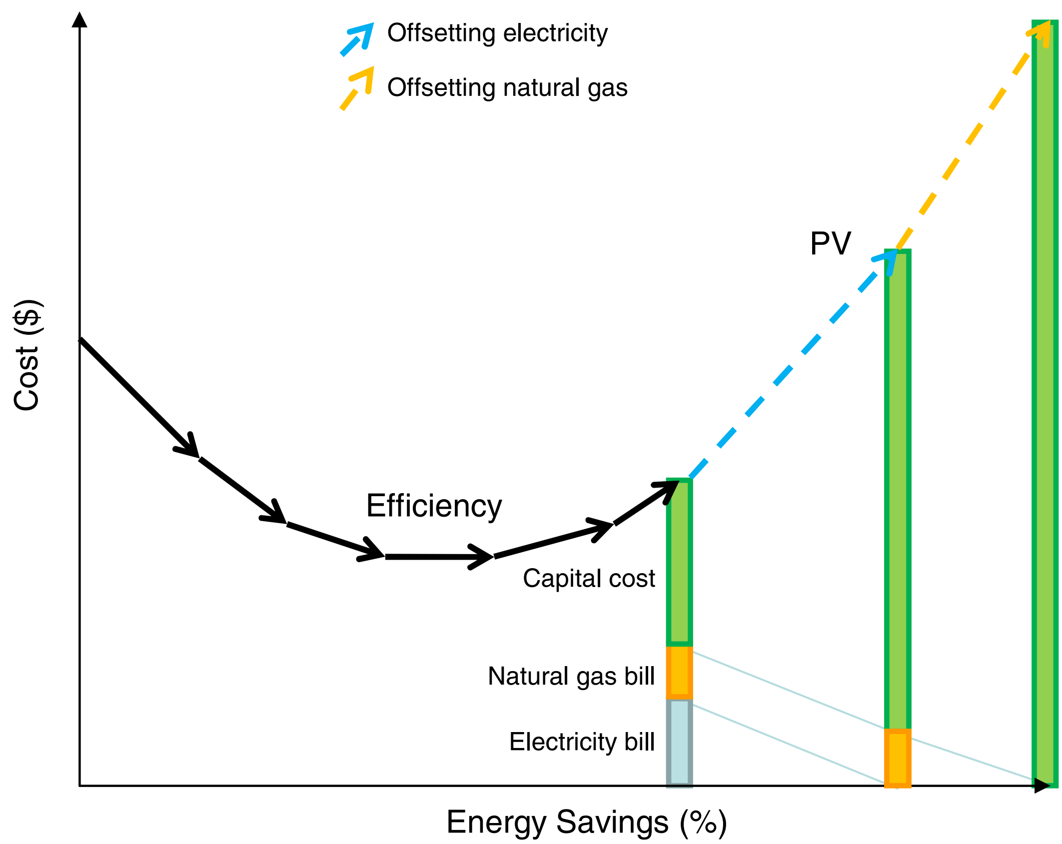

Figure 11: Non-linear PV Slope in Mixed-Fuel Optimization

Therefore the enhanced sequential search evaluates all PV options (size, azimuth, tilt) in the presence of each optimal point, as well as evaluating all efficiency measures during periods of PV purchasing. This generates a more accurate lower boundary.

V. EFFICIENCY STRATEGIES

During the development of *BE*opt, the sequential search methodology was initially refined with a focus on robustness. Various strategies can also be employed to increase the efficiency of the optimization – performing fewer building simulations to discover the cost-minimum path. As the number of search space parameters continues to grow, and because of the prospect of using EnergyPlus (25) as a simulation engine (where each building simulation takes an order of magnitude longer to run), efficiency becomes especially important.

Two approaches for increasing efficiency of the search are 1) reducing the number of simulations per iterations[3] and 2) reducing the number of iterations. Table 1 summarizes various efficiency strategies, from each approach, that will be described in subsequent sections.

[3] While reducing the number of simulations per iteration can have a secondary effect of reducing the number of iterations, it is not the primary driver.

Table 1: Listing of Efficiency Strategies

Reducing Simulations Per Iteration	Reducing Iterations
1. Modularized simulations	9. Option lumping
2. Skip superseded options	10. Forward progression
3. Skip less efficient options	11. Build up simulations
4. Skip predicted outliers	
5. Mathematically filter points	
6. Skip fine options	
7. Skip extraneous options	
8. Simulate best ranked option	

The objective is to increase optimization efficiency while limiting the impact on quality of results. Quality of results is defined as:

1. Achieving the same optimal points and lower boundary
2. Ensuring points exist at all energy savings levels across the curve (i.e. no gaps), and
3. Retaining diversity in the building measures that make up alternative designs.

These goals will be described in more detail as they relate to specific efficiency strategies.

5.1 Reducing Number of Simulations per Iteration

It is possible that not every option within an iteration needs to be, or ought to be, simulated. In the basic sequential search, there are many building designs simulated that are of little interest due to their prohibitive capital cost. Even further, one can see that there are an over-abundance of alternative building designs within even small ranges of energy savings and cost.

5.1.1 Modularized Simulations (Strategy #1)

Typical modeling practices use a single, integrated building simulation for calculating energy impacts due to building loads, hot water use, renewable energy generation, and so on. An alternative modeling approach splits the building simulation into modular components Summing each individual simulation result yields whole building energy use (and production). Assuming that each of the three simulations runs in one-third the time of the integrated simulation[4], there would be no impact on total simulation runtime if all three simulations were run for each building design.

But modularization allows for a shortcut in which runtime gains can be achieved at the expense of neglecting small interactions across the components (e.g. internal loads from hot water appliances, building temperature effects on roof-mounted PV performance, etc.) Because the sequential search evaluates building designs that are one option different than the current optimal point, only a *single* simulation ever has to be performed; the other two simulation results can be re-used from the previous optimal point.

Additionally, the number of required simulations in an optimization is further reduced because some building designs will not need any simulations performed. Three simulation results can be retrieved from various points already simulated during the optimization, thereby constructing energy use and production for the new building from previously simulated buildings. The net effect demonstrates that ignoring interactions via a modular approach reduces simulation runtime to less than one-third that of an integrated approach.

[4] The actual impact on runtime is specific to which simulation engines are used in the modular and integrated approaches.

The actual number of simulations performed with each simulation engine can vary between optimizations and is dependent on a number of factors like the specific building measures available in the parameter search space[5]. This indicates that two optimizations with the same number of efficiency measures under evaluation can have a different mix of simulations (e.g. number of DOE-2 simulations vs. number of TRNSYS simulations) and consequently differing runtimes.

The applicability of modularization may be specific to the user's simulation engines. Each simulation engine has its short-comings, such as speed of simulation, accuracy, or modeling capabilities. *BE*opt, for example, utilizes a loads/HVAC simulation in DOE-2, a hot water simulation in TRNSYS, and a PV simulation in TRNSYS in order to take advantage of each simulation engine's respective strength.

5.1.2 Skip Superseded Options (Strategy #2)

Superseded options refer to those options that were in a given optimal point's building description at one point but have since been replaced by more efficient options. The invest/divest special case robustness strategy involved searching these superseded options for possible optimal points that might otherwise be missed. This efficiency strategy evaluates the impact of inactivating that robustness strategy to various degrees.

Variants

One variant of this strategy involves skipping superseded options *except* for the last superseded option in a category. So, for example, if the optimization has proceeded from single clear glazing to double clear glazing to low-e glazing, the sequential search

[5] For this reason, efficiency gains for strategies presented later in this document will be defined in terms of reduction in number of simulations rather than reduction in runtime.

will continue to evaluate the double clear superseded option. This essentially provides a bridge back to the less efficient options such that the search can revert to the double clear option in one iteration and then to the single clear option in the next, without having to simulate both options in every iteration.

In another variant, the strategy applies only to well-ordered categories. Well-ordered categories are those whose options can be ordered from least to greatest energy savings independent of climate, building geometry, and other efficiency measures. In categories that are not well-ordered, there is the possibility of an option being superseded by another option but later have an improved benefit-cost ratio as other efficiency measures are introduced into the building (with which the superseded option interacts).

Table 2: Variants of Skip Superseded Options Strategy

	Variant
2a	Base
2b	Simulate last superseded option
2c	Apply to well-ordered categories

5.1.3 Skip Less Efficient Options (Strategy #3)

This strategy, which applies solely to well-ordered categories, involves the notion that only options of increasing energy efficiency are of interest the further the optimization proceeds. Similar to the previous strategy, it entails skipping less energy-efficient options whenever possible. For example, if the optimal points jump from including R-13 walls to R-21 walls, all wall options less efficient than R-21 (say, R-13 and R-19 options) will be skipped. This strategy therefore skips both superseded options (R-13, in the example) as well as those options that have been leapfrogged (R-19).

Variants

Similar to the variant in the preceding section, variants of this strategy also attempt to provide a bridge backwards to less efficient options. This can involve simulating the single less efficient option, simulating a random less efficient option, or cycling through all less efficient options (one per iteration). Additionally, an interesting hybrid variant entails skipping less efficient options except for the last superseded option.

Table 3: Variants of Skip Less Efficient Options Strategy

	Variants
3a	Base
3b	Simulate less efficient option
3c	Simulate random less efficient option
3d	Simulate cycled option
3e	Simulate last superseded option

5.1.4 Skip Predicted Outliers (Strategy #4)

Within the universe of possible building, only points near the cost-minimum boundary of the curve are of primary importance. Stated another way, points found outside this lower band ought to be avoided whenever possible. These outlying building designs have little benefit and represent wasted simulations.

One way to filter out these points involves keeping track of the most current information about every option to make judgments about whether future building designs should be simulated. For example, the search would run a full iteration and store incremental energy savings and costs between each point and the previous optimal point. Then each point in subsequent iterations would have its energy savings and costs predicted based on the stored information to determine if it is expected to fall within some X% of the lower boundary's cost (Figure 12).

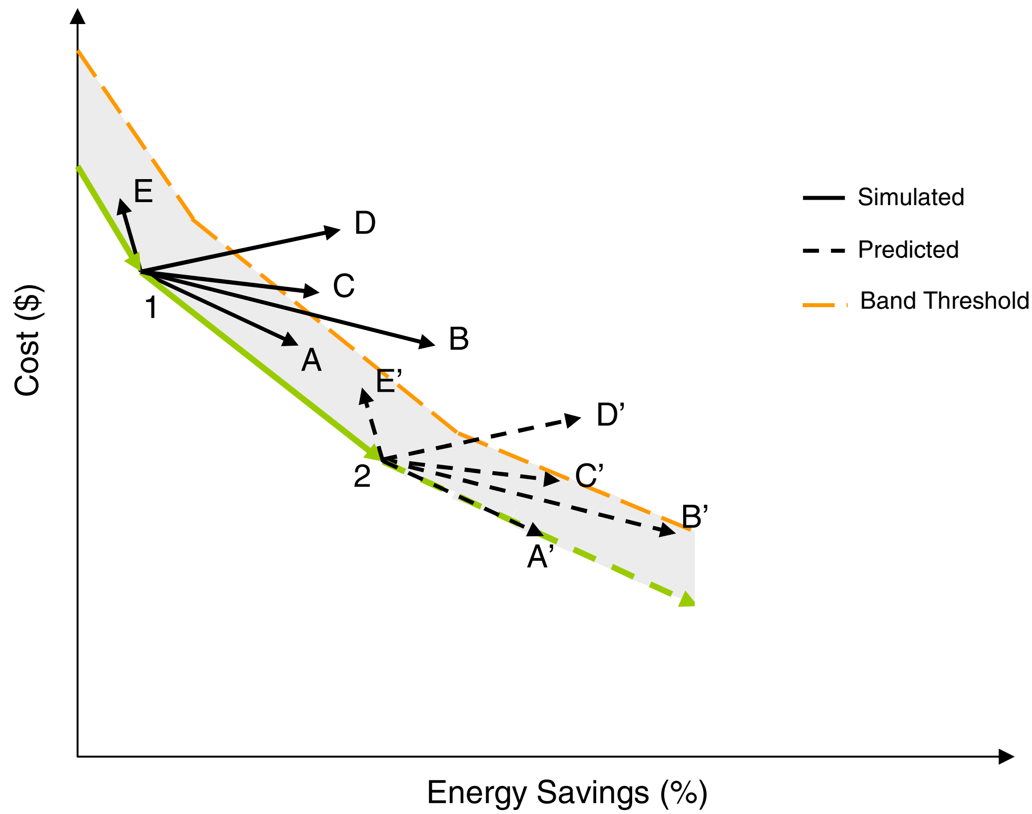

Figure 12: Illustration of Skip Predicted Outliers Strategy

If the point is predicted to have positive energy savings (points A' through D'), there is not an actual lower boundary to use. Therefore, the predicted point that achieves the steepest slope (point A') is used as the predicted lower boundary, and subsequently, the threshold for comparison. If the point is predicted to have negative energy savings (point E') relative to the previous optimal point, the actual simulated lower boundary, as shown between optimal points 1 and 2, can be used to specify the threshold with which to compare.

Incremental energy savings and cost predictions are updated upon the completion of each iteration in order to best reflect the current situation. For example, suppose that R-21 wall insulation was found to achieve 10% energy savings and cost $100 relative to the optimal point's R-13 option. If the sequential search chooses a R-19 option for the next optimal point, the incremental values for the R-21 option must be updated for this new reference. The difference in incremental predictions for the R-19 option (relative to R-13) is thus subtracted from the incremental predictions for the R-21 option (also relative to R-13) – this generates incremental energy savings and cost predictions for the R-13 option relative to the optimal point's R-19 option.

Variants

Variants of this strategy involve altering the band tolerance such that a wider, or narrower, target band is used. Lower band tolerances will achieve higher efficiency gains, but at increased risk of finding suboptimal building designs. Other variants could entail variable tolerances such that the band tolerance is set more aggressively for regions of energy savings that are of less interest for the user and more conservatively for the user's target energy savings region.

Table 4: Variants of Skip Predicted Outliers Strategy

	Variants
4a	5% band tolerance
4b	3% band tolerance
4c	2% band tolerance
4d	Increased tolerance for target energy savings region

5.1.5 Mathematically Filter Points (Strategy #5)

It is possible that simulations can be avoided by determining that steeper slopes cannot be attained for certain options with high capital costs compared to simulated options with lower capital costs and known energy savings. Starting with a simple illustration, suppose that energy efficiency options in the window distribution and ceiling insulation categories are to be evaluated in an all-electric building. The sequential search first runs the starting point: window distribution option 1 (equal window area on each façade) and ceiling option 1 (R-30 insulation). Next, it evaluates window distribution option 2 (shifting some window glazing area from the north facade to the south façade). As shown by vector 1 in Figure 13, the slope from starting point to this point equals the slope of the cost-of-electricity line since a change in window distribution does not increase building cost.

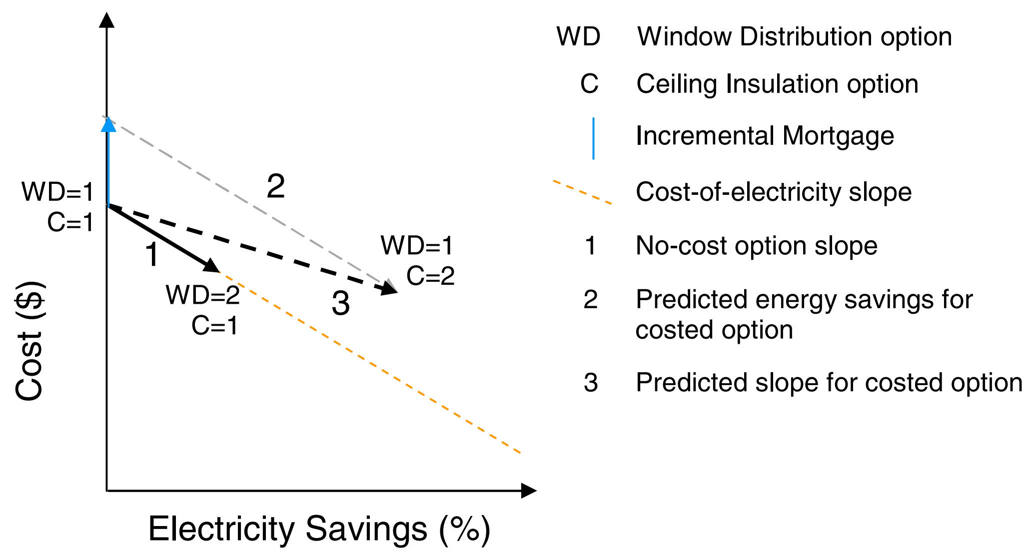

Figure 13: Costed vs. No Cost Option, All-Electric Optimization

Next the sequential search evaluates ceiling option 2 (replacing R-30 insulation with R-40). This option includes a capital cost increment, as shown by the blue vertical line.[6] It is known that an increase in ceiling insulation will reduce heating, cooling, and fan consumption.[7] Prior to its building simulation, the actual amount of electricity saved by ceiling option 2 is unknown, therefore the most conservative assumption possible needs to be made – reducing heating, cooling, and fan electricity usage to zero (vector 2). From visual inspection, the resulting vector for the ceiling option (vector 3) cannot achieve a steeper slope than the window distribution option (vector 1) despite the over-conservativeness of the energy savings prediction. In fact, costed efficiency options can

[6] *BE*opt generates capital costs for geometry-related options without performing a building simulation. Other software tools that explicitly use the output file of building simulations in order to determine geometry cost multipliers (wall and window areas, for example) will not be able to utilize this strategy.

[7] In *BE*opt, whole building energy use is divided into multiple end uses: heating, cooling, fans, hot water, lighting, and miscellaneous, with each end use further divided into electricity and natural gas. The end uses that a specific option affects (heating, cooling, and fans in the case of ceiling insulation) can be determined from the first full iteration of simulations.

never achieve a steeper slope than no cost options under this situation. Thus, for an all-electric building, simulations for all costed options can be avoided whenever no-cost options achieving energy savings are available within an iteration.

Another simple example demonstrates the applicability of this procedure to two costed options. Figure 15 illustrates that even between two costed options, it can be mathematically determined if the higher capital cost option can achieve a steeper slope than the lower capital cost option. Here, the low-cost option is simulated and achieves the slope shown by vector 1. As before, the high cost option has known capital costs. The end uses affected by this option are again reduced to zero (vector 2) as an over-prediction of possible simulated energy savings. The resulting vector 3 does not achieve a steeper slope than vector 1 for the low cost option; therefore the simulation for this high cost option can be avoided.

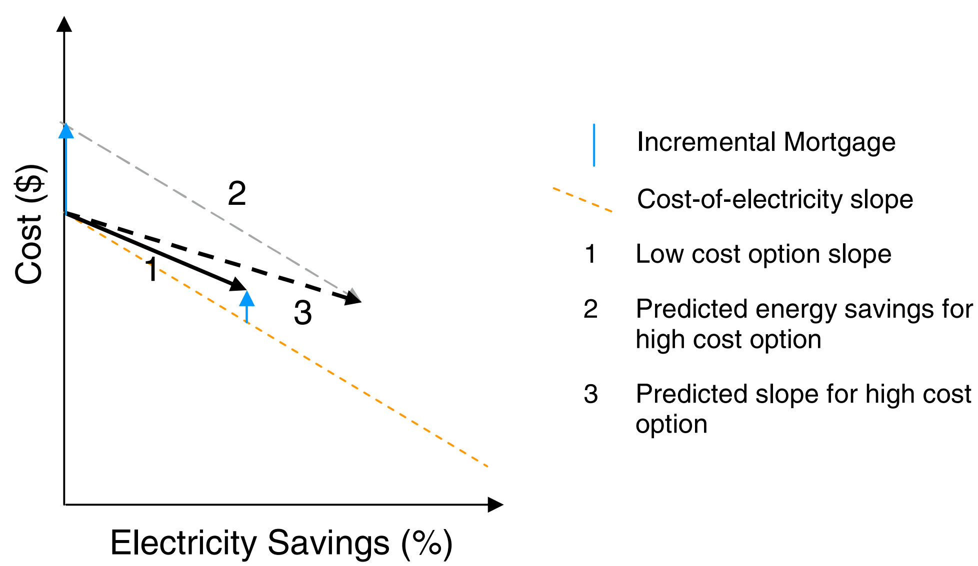

Figure 14: High Cost vs. Low Cost Option, All-Electric Optimization

The above examples of mathematically filtering options based on predicted energy savings hold true only if a single fuel type is available across the parameter space

– i.e. for an all-electric building. But if the building includes a gas furnace, for example, efficiency measures would impact both electricity and natural gas consumption.

A given building simulation point, without incremental capital cost, under this mixed-fuel scenario could be located at a number of different positions depending on its natural gas and electricity consumption impacts. The point could fall along the cost of natural gas line if it only impacts natural gas (Figure 15a), the cost of electricity line if it only impacts electricity (B), or somewhere in between the two lines depending on the specific mix of natural gas and electricity saved (C). Additionally, points can fall outside the two cost-of-fuel lines by swapping fuel use, which results in an increase in one fuel type energy use and a decrease in the other (D). Note that fuel swapping occurs in two situations: 1) direct fuel switching, for example when an electric water heater is swapped for a gas water heater, and 2) indirect fuel switching, such as an increase in electric space cooling and a decrease in gas space heating due to a more efficient appliance in a heating climate.

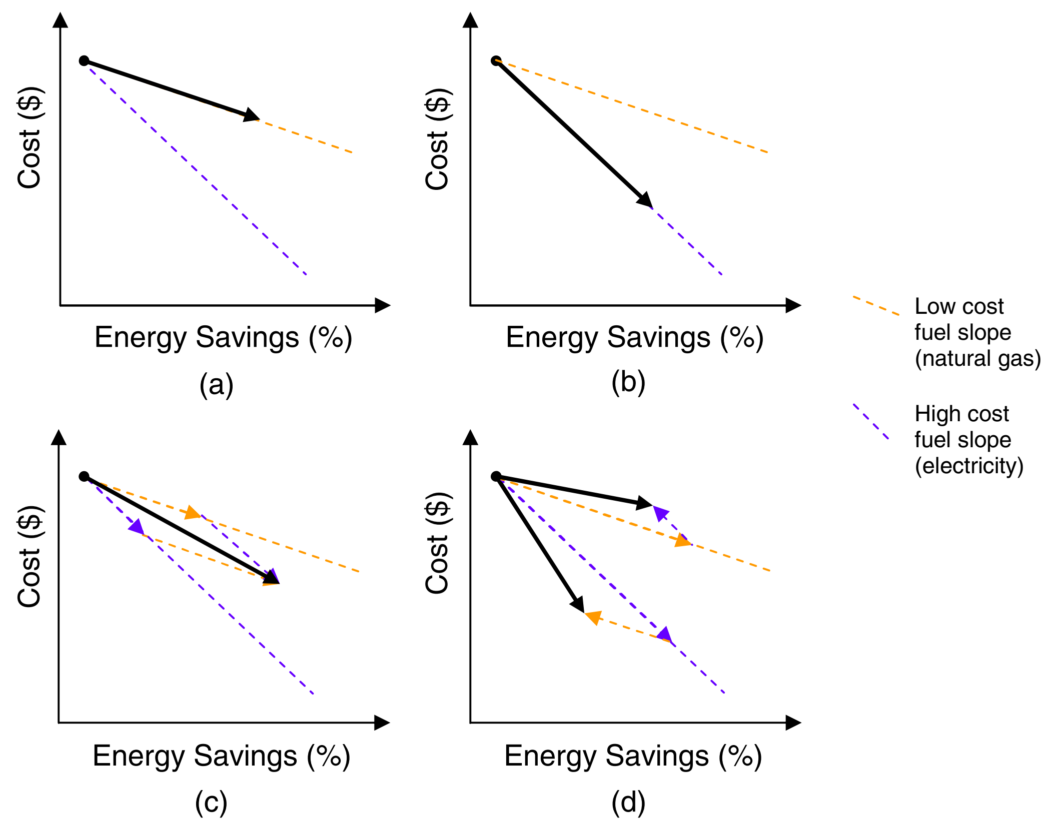

Figure 15: Point Scenarios for Mixed-Fuel Optimizations; (a) low cost fuel savings, (b) high cost fuel savings, (c) low and high cost fuel savings, (d) fuel swapping

Unlike the two previous simple illustrations, a more general approach is therefore required to accommodate optimizations involving mixed fuels. The first step involves performing a single full iteration from the starting point. For each point of the iteration, affected end uses (e.g. heating, cooling, and fan end uses for higher ceiling insulation R-values) are identified. As per basic sequential search operation, the steepest slope is chosen as the next optimal point.

In subsequent iterations, incremental capital costs are calculated for each option relative to the previous optimal point and then sorted from least to greatest. Building simulations are performed option by option until one achieves positive energy savings relative to the previous optimal point; this point's slope becomes the basis for future comparisons. Each ensuing point in the iteration passes through a filtering algorithm to determine if its energy use predictions can achieve a slope steeper than the current steepest slope of the iteration.

First, if affected end uses for the high cost fuel exist, they are reduced to zero in order to achieve maximum energy savings. If the slope of this resulting vector (Figure 16a, line 2) is steeper than the current steepest slope (line 1), the point ought to be simulated because it's possible for the building simulation to achieve a steeper slope.

Secondly, if affected end uses for the low cost fuel also exist, the fuel swapping scenario is evaluated. After reducing the high cost fuel end uses to zero above, low cost fuel end uses are then increased to the point where cumulative energy savings across affected end uses is zero (Figure 16b). If the y-value of this point is less than the y-value of the previous optimal point, the point should be simulated. If neither scenario's criterion is met, the point's simulation can be avoided.

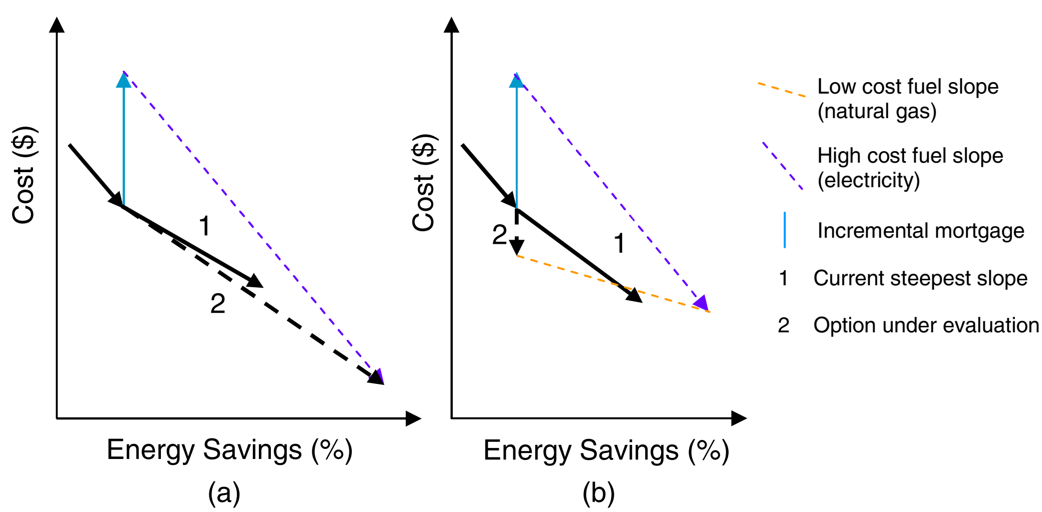

Figure 16: Required Comparisons for Mathematically Filter Points Strategy; (a) high cost fuel savings, (b) fuel swapping

For the majority of building efficiency measures, this strategy will over-predict the steepness of the slope compared to the slope that would result from an actual simulation. For example, if an option were to increase gas heating and reduce electric cooling (due to changing the building load), and electricity was the high cost fuel, the mathematical filtering algorithm would reduce the electric cooling end use to zero and increase the gas heating end use by the same amount. The likelihood of this outcome actually occurring in the simulation (the cooling load decreasing to zero and the heating load drastically increasing) is very low. Similarly, if an option yields a reduction in gas water heating, the filtering algorithm would evaluate the possibility where gas water heating is decreased all the way to zero - also an unlikely outcome. Therefore this approach is very conservative for most options.

On the other hand, this approach is not conservative for the subset of fuel switching measures. A switch from electric water heater to gas water heater would result in a prediction of electric water heating decreasing to zero and gas water heating increasing by the same amount – which is precisely what would occur.

However, there is an important, overlooked problem: when a building efficiency measure causes a reduction in building load, there may be capital cost savings due to downsizing the heating and cooling equipment. The strategy cannot accommodate these savings since the potential downsizing is unknown prior to running the building simulation. In the discrete world, even the smallest incremental efficiency option can cause downsizing of HVAC equipment. The robustness of this efficiency strategy will be influenced by the degrees to which overly conservative energy savings predictions and possible HVAC re-costing come into play.

Variants

There are a few variants that can attempt to handle the cost savings due to HVAC resizing, which is the fundamental problem with this strategy. One variant involves establishing a linear relationship between energy savings and HVAC re-costing and simply applying it to the mathematical calculations. This is, of course, a very crude approximation since the downsizing of HVAC equipment is discrete and not continuous.

Another variant uses an HVAC sizing algorithm prior to, and independent of, the building simulation such that the actual cost savings (or a very close approximation) can be used. The runtime associated with performing these HVAC sizing calculations must be taken into account in order to determine if this is a worthwhile endeavor.

Table 5: Variants of Mathematically Filter Points Strategy

	Variants
5a	Base
5b	Linear relationship between energy savings and HVAC downsizing cost savings
5c	Independent calculation of HVAC size

5.1.6 *Skip Fine Options (Strategy #6)*

Optimization runtime is intimately tied to the number and range of options within the parameter space. Plug-in lighting, for example, comprises a very small percentage of total building energy use. Varying lighting options at the start of an optimization by, say, 10% CFLs, can result in nearly identical energy use. While the user can exhibit control over the fineness of options included in an optimization, having an approach that automatically reduces this fineness would be beneficial to many users.

After the first full iteration in the optimization process is performed, options within certain flagged categories are searched for energy savings values that fall within a specified tolerance[8] of each other (options B and C in Figure 17). If such options are found, the option with the greater capital cost (option C) is marked for exclusion from future iterations as it is merely offset vertically from the lower cost option (B) and should never achieve a steeper slope in future iterations.

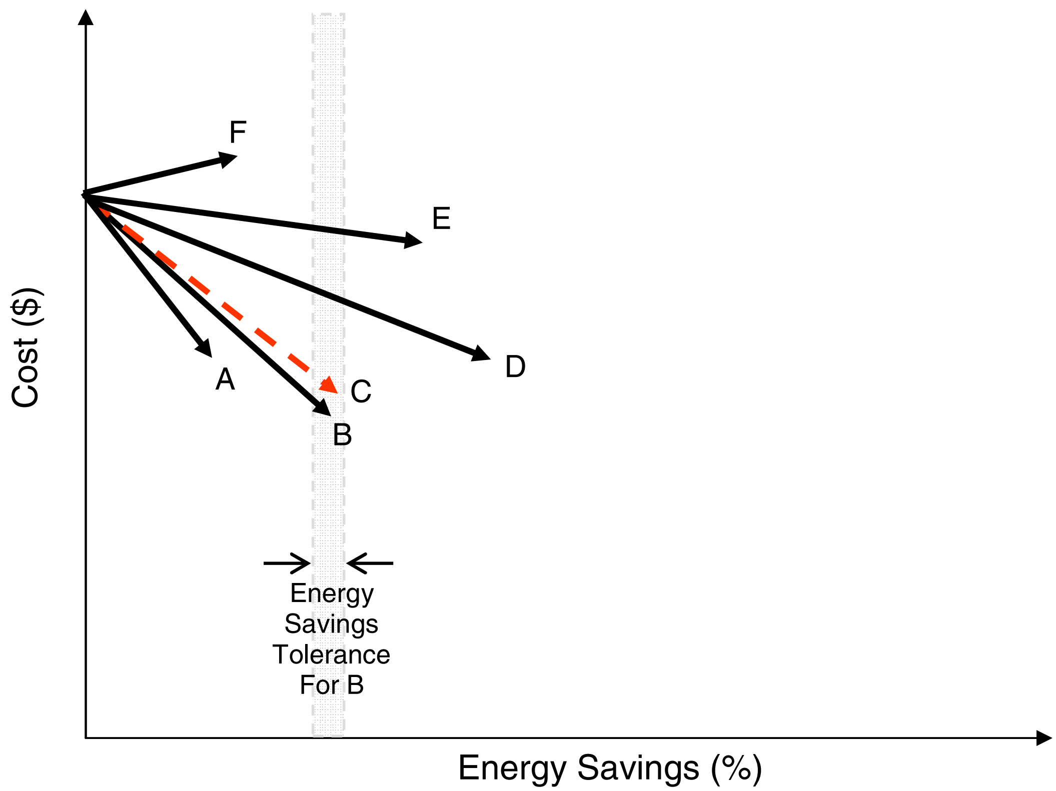

Figure 17: Illustration of Skip Fine Options Strategy

Categories must be flagged in advance to represent that differences in energy use between the category's options stay fixed or decrease regardless of how the building evolves during the optimization. If two wall constructions of similar R-value were

[8] Tolerances are technically set on both whole building energy use and individual end uses in order to account for fuel-swapping options.

evaluated at the beginning of an optimization, for instance, and were found to achieve similar energy savings, one would expect the difference in energy savings to further decrease as additional efficiency measures are introduced into the optimization. On the other hand, two building orientations that have similar energy savings at the beginning of an optimization may diverge as other options, like window area distribution, are selected by the optimization. Therefore, the walls category would be evaluated for fine options while the building orientation category would not.

Variants

The basic strategy allows skipping fine options assuming these options are within the same category (e.g. two plug-in lighting options). A variant of the strategy involves reducing simulations across categories for options with essentially equivalent energy savings. For example, suppose that a wall option and ceiling option are found to achieve essentially equivalent across all of their end use results. Because both are envelope measures (affecting building UA), the difference in energy savings between the two will be reduced as the optimization proceeds due to decreasing loads as the building becomes more efficient. While it makes little sense to skip the wall or ceiling option from the entire optimization, since these options are not mutually exclusive, the strategy could skip the option with higher capital cost until the option with lower capital cost is first chosen by the search. This variation in strategy can be applied across UA categories and possibly across appliance/lighting categories (but not across both UA and appliance categories).

Table 6: Variants of Skip Fine Options Strategy

	Variants
6a	Base
6b	Cross-category application

5.1.7 Skip Extraneous Options (Strategy #7)

Extraneous options are those that fall above the lower boundary of a category's cost curve. For example, suppose that wall insulation options are plotted on a graph of capital cost versus R-value, as demonstrated in Figure 18a. Assuming that energy savings are proportional to R-value, the most cost-effective selection of wall options would be proceeding from option A to B to D, skipping any options that fall above the cost curve lower boundary (option C).

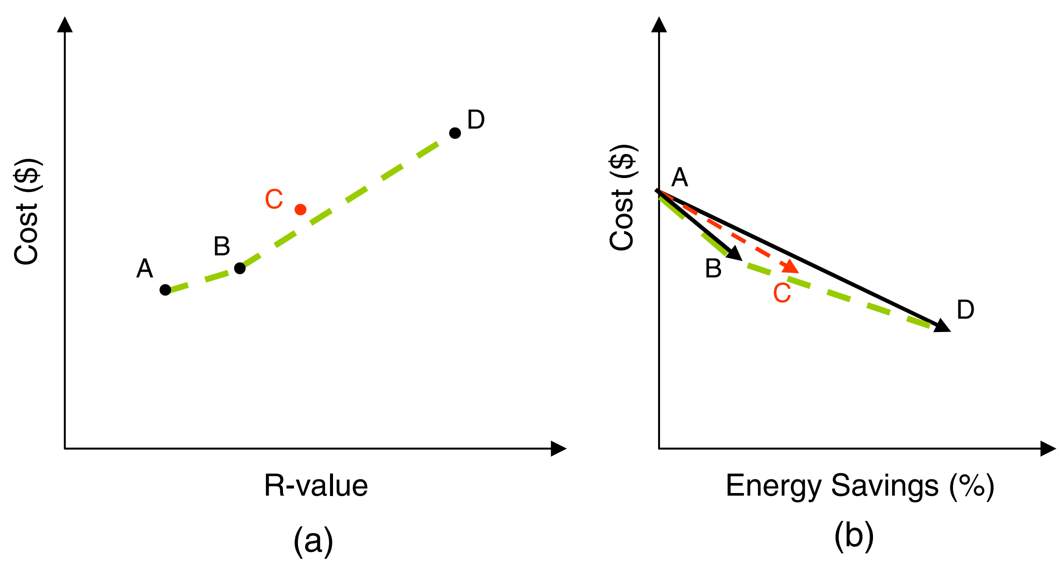

Figure 18: Illustration of an Extraneous Point within a Category; (a) cost-curve, (b) energy savings curve

While R-values are specific to insulation categories, the same idea can be applied more generally to all categories by using energy savings values from a full sequential search iteration (Figure 18b). Here, one can determine extraneous options within a category by performing an iterative evaluation of progressive slopes. Because all options are within the same category, switching from one option to another involves substituting the second option for the first[9]. Procedurally, the sequential search first evaluates slopes between each option and option A; the steepest slope is selected (option B). Subsequent slopes are now evaluated between each option and the previously selected point, again with the steepest slope chosen (option D). Extraneous options are defined as those options that are skipped during this iterative process of calculating progressive slopes.

Variants

In order for the extraneous point to remain an outlier in subsequent iterations, the relative energy savings for each option should stay rather proportional throughout the optimization. For example, other efficiency improvements to the building will cause the energy savings for an envelope (UA) option to decrease, but all options within the UA category should decrease proportionally, excluding second-order effects. In essence, this should cause Figure 18b to simply compress horizontally. Other well-ordered categories (e.g. appliances, lighting, HVAC equipment) will approximately compress proportionally as well and may still result in high levels of robustness.

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[9] This differs from the description of the sequential search process (Figure 3) where efficiency measures are assumed to be from different categories such that their vectors are additive, not substitutive.

Table 7: Variants of Skip Extraneous Options Strategy

	Variants
7a	Apply to UA categories
7b	Apply to well-ordered categories

5.1.8 *Simulate Best Ranked Option (Strategy #8)*

A zealous efficiency strategy entails simulating only the single, next ranked option within a category based on an option ranking developing during the first iteration of the search.[10] As demonstrated in Figure 19, the strategy uses the same iterative process as that used for identifying extraneous points in the previous section, but now the focus is on ranking each option within its category. The options are ranked by progressive slopes such that option A is ranked first, option B second, and option D last[11].

After the options in certain category have been ranked, the sequential search will only evaluate the next ranked option within an iteration. So, if the current building design includes option A from Figure 19, only option B of the options in this category would be evaluated at this point in time. Once option B is chosen for inclusion in the building, option D would be the only option evaluated in this category.

[10] This is similar to the simple optimization method described in Section 3.4, but that method created a single ranking across all categories whereas this method creates an individual ranking for each category.
[11] Option C, the extraneous option described in Section 5.1.7, will again be discarded from the search as the strategy of skipping extraneous points is inherently a subset of this strategy.

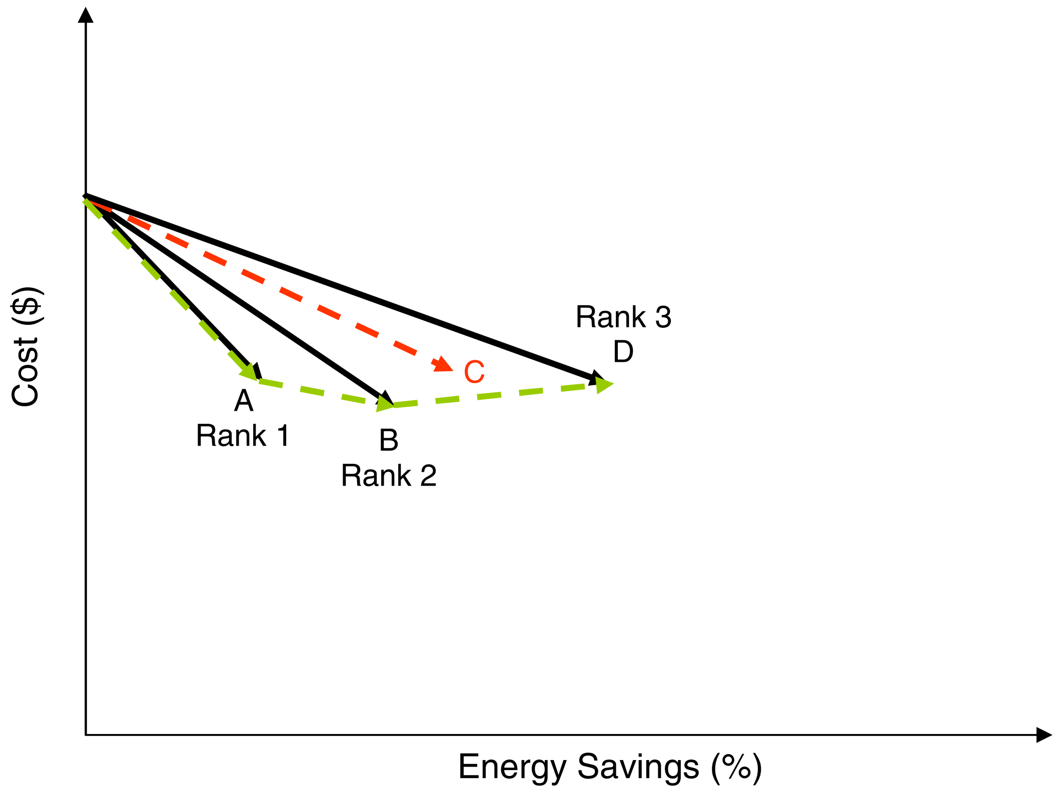

Figure 19: Illustration of Progressive Ranking Process within a Category for Simulate Best Ranked Option Strategy

Variants

It is clear that this approach should not be applied across all categories because the ranking of options within certain categories, like orientation or window type, would not be constant throughout a given optimization. Therefore, the variants once again involve applying the strategy either to well-ordered categories or UA categories (the more conservative subset), where the likelihood of the rank order remaining constant for the latter is greater.

Additional variants might involve deciding how many, and which, ranked options should be evaluated in a given iteration in order to improve search robustness. For example, one variant could dictate evaluating the two next best ranked options. Likewise, another variant could also evaluate two ranked options, but instead could use the next and previous best ranked options.

Table 8: Variants of Simulate Best Ranked Option Strategy

	Variants
8a	Apply to UA categories
8b	Apply to well-ordered categories
8c	Simulate next two best ranked options
8d	Simulate next best and previous best ranked options

5.2 Reducing Number of Iterations

The following strategies attempt to reduce the number of iterations required to generate the lower-boundary curve.

5.2.1 Option Lumping (Strategy #9)

Option lumping recognizes that valuable information from an iteration exists that is not currently used in the sequential search methodology. In the absence of interactions between building measures, one could simply rank the options of the first iteration from best (steepest downward slope) to worst and then string them together in order of rank to correctly represent the lower boundary curve – the first optimal point would include the best ranked option, the second optimal point would add the second best ranked option, and so on.

However building measures do have interactions, and so the options' actual energy use and rank-order varies as other efficiency measures are introduced into the optimization. Nevertheless, an effective optimization strategy to reduce the number of simulations may be to string together, or lump, a certain number of options (e.g. 3) as shown in Figure 20.

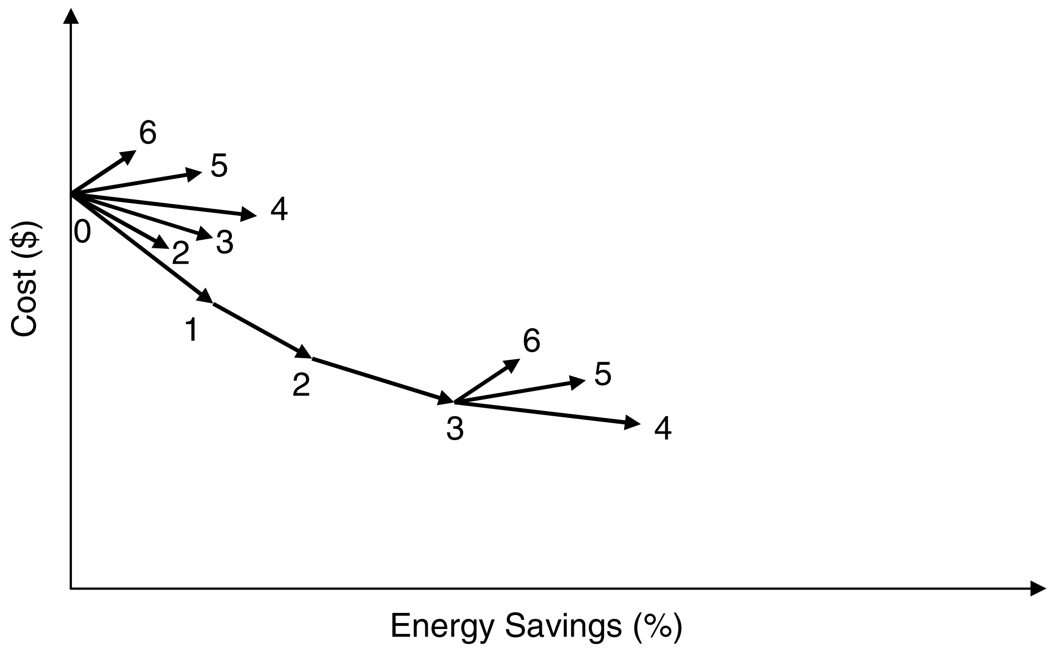

Figure 20: Option Lumping Strategy

Variants

One variant allows lumping options while attempting to adhere to the second quality goal that requires achieving points at all energy savings levels across the curve. To meet this end, the variant would allow lumping points while the lumped points' cumulative energy savings from simulations is less than a specified limit (such as 5% or 10%).

On top of this constraint, additional criteria could be set based on the observations that options achieving very small energy savings tend to have little impact on other measures while options achieving large energy savings tend to cause larger interactions. Therefore, options that achieve very little energy savings (so-called "tiny" points) could always be lumped, regardless of whether they cause cumulative energy savings to exceed the limit. On the other hand, options that achieve energy savings greater than the cumulative energy savings limit ("large" points) could be lumped if only tiny options have thus far been lumped. Since the option represents an unavoidable large gap that would otherwise simply be chosen in the subsequent iteration, lumping the option now can save an extra iteration's worth of simulations. The constraint to lump if only tiny options have currently been lumped helps ensure that the currently lumped options have negligible impacts on this large option.

Another constraint involves the potential benefit of imposing a limit on the number of options that can be lumped together. As the number of lumped options increases, there is a greater likelihood that search will deviate from the true lower boundary. The strategy is only applied to non-tiny points with the notion that 1) tiny points will have very little impact on the current situation and 2) practically speaking, the number of tiny options included in a search space should tend to be very low.

An alternative variant involves lumping all options whose slopes are within a certain tolerance of the steepest slope of the iteration. For example, referring back to the idea presented in Section 5.1.5 that no-cost options must have equal slopes in an all-electric optimization and similar slopes in a mixed-fuel optimization, this strategy would effectively allow many no-cost options to be lumped together. Note that this variant could produce gaps in the optimization output and perhaps should be coupled with the cumulative energy savings constraint.

Table 9: Variants of Option Lumping Strategy

	Max cumulative energy savings	Always lump tiny points	Include large point	Max number of non-tiny points
9a	5%	No	No	Infinite
9b	10%	No	No	Infinite
9c	5%	Yes	Yes	2
9d	5%	Yes	Yes	3
9e	5%	Yes	Yes	Infinite

5.2.2 *Forward Progression (Strategy #10)*

This strategy forces the sequential search to proceed towards greater energy savings even if there is a better point achieving negative energy savings from the current optimal point. Unlike strategies where less efficient options were skipped (e.g. strategies 2 and 3), this strategy simulates all of the options within an iteration; it simply will not choose an option of lesser efficiency for a given optimal point. Whenever the strategy chooses an alternative optimal point to the basic sequential search methodology, the path must diverge to some extent from the true cost-minimum path.

If choosing points of reduced energy savings results in only a slightly more optimal solution, the search may be better off saving these extra simulations and continuing along the path of forward progression. As illustrated in Figure 21, suppose that points 2 and 2' were simulated from optimal point 1. The basic sequential search would select point 2' as the next optimal point and continue subsequent iterations from this point on. The forward progression strategy, however, would choose point 2 as the next optimal point because point 2' does not have positive energy savings. In this example, the forward progression strategy will save two iterations of simulations (iterations 2' and 3') but neglect to find point 3' as an optimal point.

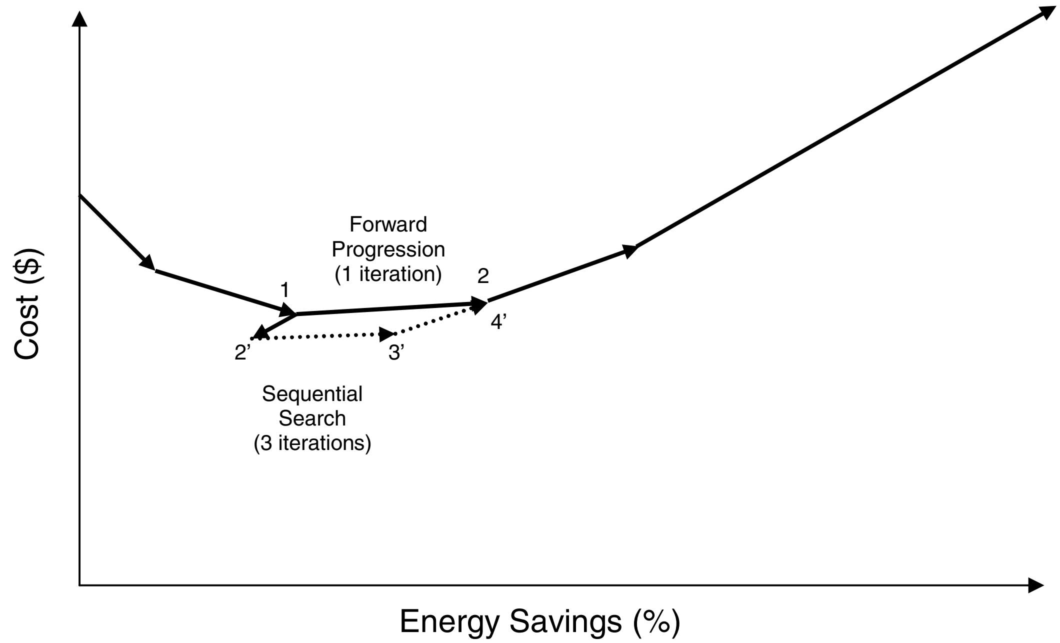

Figure 21: Illustration of Forward Progression Strategy

5.2.3 *Build Up Simulations (Strategy #11)*

This strategy makes use of the modularized modeling approach to provide additional building designs that the sequential search would not otherwise dictate simulating. By creating combinations of all three simulation results to "build up" new simulations, a number of points can be added into the optimization without having to perform any additional building simulations. The notion is that one of these new building simulation points could find the optimal path sooner than proceeding one option at a time would.

However, the number of combinations grows exponentially with larger optimizations and creating all of these combinations from retrieved simulation results will likely have a negative impact on runtime (as well as storing/graphing so many points in graphing software). Therefore, any implementation of this strategy must somehow devise an approach for reducing the number of combinations to be evaluated.

Variants

Perhaps a useful implementation of this strategy would involve post-processing these built-up simulations after the optimization is complete and only based on user-selected efficiency measures of interest. Similarly, efficiency strategies like skipping superseded or less efficient options, which result in a lack of building designs with inefficient options at high levels of energy savings, could be supplemented with these additional building designs to provide more diversity.

VI. RESULTS AND DISCUSSION

In this chapter, a test suite will be developed to determine the effectiveness of each strategy. Based on the results of the individual strategies, packages of strategies can be constructed that span various levels of robustness and efficiency.

6.1 Test Suite

The test suite is comprised of eighteen optimizations: small, medium, and large-sized optimizations (size of the parameter space) for six climates: Phoenix, Houston, Atlanta, San Francisco, Boulder, and Chicago. Small optimizations are further split into two groups: three optimizations where the parameter space is finer (standard and relatively efficient options) and three optimizations where the parameter space is coarser (standard and very efficient options). Large and medium-sized optimizations inherently contain both fine and coarse options.

Each optimization uses state-average electricity and natural gas rates based on Energy Information Administration (EIA) data. The building is 2500 square feet, 2-stories, with a two-car garage and a gable roof with 6:12 pitch. The specific details of each optimization, including the specific range of efficiency options in the search space, can be found in Appendix A.

The optimizations use *BE*opt source code modified for each specific robustness or efficiency strategy. If not specified, default *BE*opt values are used; these include objective function (first year cash flow plus annualized replacement costs), option cost assumptions (typically RS Means or manufacturer's data), source-to-site ratios for electricity and natural gas (3.16 and 1.02, respectively), and option simulation models.

Simulations are performed using DOE-2's DESIGN-DAY method for auto-sizing; 99% heating and cooling design temperatures are derived from ASHRAE (26) (and obtained from the .stat files that accompany the EnergyPlus EPW weather files). For costing purposes, the continuously sized equipment is then discretized to the next largest available size in 0.5 ton (for the air conditioner) and 20kBtu/hr (for the furnace) increments. Additional information about the test suite, including the DOE-2 BDL code for the design day specification for HVAC sizing, can be found in Appendix A.

6.2 Characterization of Results

Results for a given robustness or efficiency strategy will impact both robustness and efficiency of the search. Efficiency gains are expressed as the percent of saved simulations relative to the number of simulations in the reference optimization. Robustness values, expressed as percent average deviation and percent maximum deviation, characterize the variation in lower boundary curves between the efficiency and reference optimizations. The values for both average and maximum deviation are obtained by taking the difference in lower boundaries between a given optimization and its corresponding reference optimization at polled 5% source energy savings levels, as illustrated in the figure below.

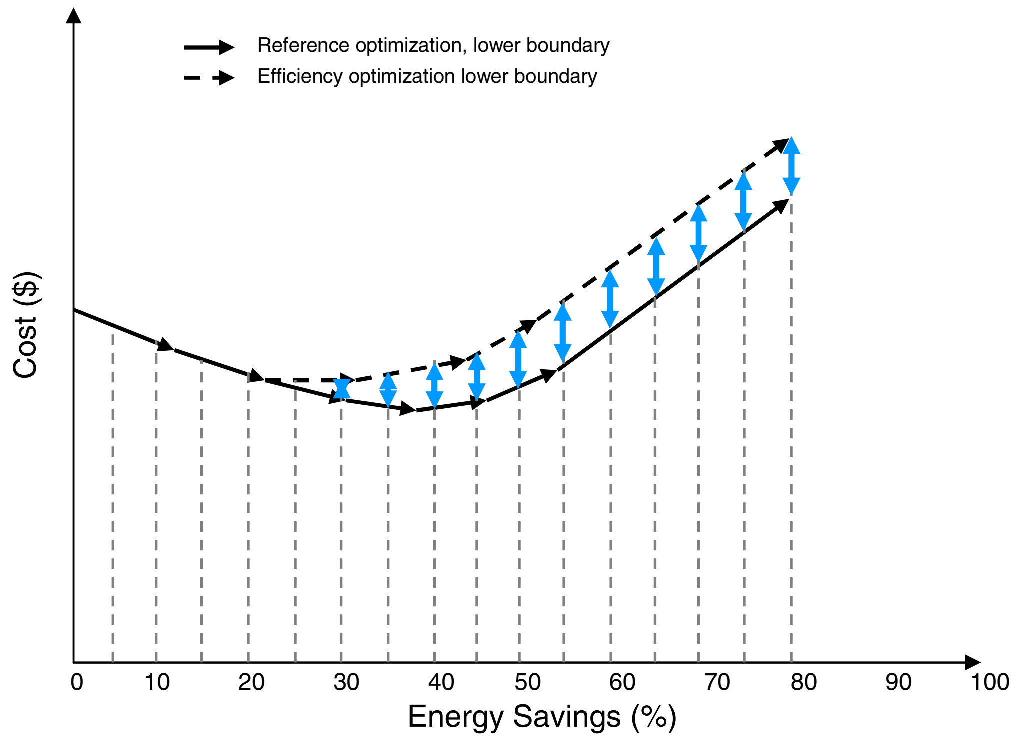

Figure 22: Illustration of Maximum/Average Deviation for Efficiency Optimizations

The average deviation of a specific optimization is the sum of all the polled differences in lower boundaries, denoted by the vertical arrowed lines, divided by the number of polled energy savings levels, and then expressed as a percent of the optimization's starting point y-value. The maximum deviation is the greatest difference at any polled energy savings level again as a percent of the optimization starting point's y-value. For the vast majority of optimizations, the maximum deviation occurs at the end of the efficiency curve (as shown in the above illustration) and is therefore replicated across the stretch of PV generation.

6.3 Robustness

6.3.1 Strategies Evaluated

The robustness strategies that do not involve user interaction were implemented in order to determine their effectiveness at identifying more cost-effective optimal building designs; indeed, the invest/divest and large-step special cases are currently included in the BEopt software tool's sequential search. Since the effectiveness of the solution for the positive interaction special case, which allows a user to explicitly include building option combinations in the search strategy evaluation, is wholly dependent on the user's choice of options, it will not be assessed.

6.3.2 Results

There are several methods of quantifying the effectiveness of the robustness strategies. The first entails identifying the occurrence of special cases within the test suite optimizations to demonstrate that such situations do arise. The second method calculates the efficiency gains and average/maximum deviations for each optimization. And the final method validates the optimization against an extensive parametric to ensure that the optimization methodology discovers the true cost-minimum optimal points.

Occurrence of Special Cases

The results of all eighteen reference optimizations were inspected for the identification of special cases. By looking at both orphaned and non-orphaned optimal points chosen by an optimization, one can observe the occurrence of the two special cases implemented:

1. Invest/divest special case - If an option number from a given category reverts to an earlier chosen option number, a superseded option must have been selected.
2. Large-step special case – If a given iteration's optimal point differs from the previous optimal point by more than one option, the given optimal point must have come from a previous iteration (since the basic sequential search only evaluates buildings one option different than the previous optimal point).

The table below lists the occurrence of these invest/divest and large-step special cases for large optimizations. Appendix B further details all of the optimal points for each optimization and illustrates the occurrence of special cases.

Table 10: Number of Invest/Divest and Large-Step Special Cases for Large Optimizations

Special Cases	# Invest/Divest	# Large-Step
Phoenix	13	6
Houston	8	3
Atlanta	22	8
San Francisco	25	11
Boulder	23	8
Chicago	13	4

Efficiency Gains and Deviations

Next, efficiency gains and maximum/average deviations for the two robustness strategies were calculated. The two robustness optimizations are compared against reference optimizations that include both robustness strategies (as this is the current sequential search implementation found in *BE*opt). Therefore, it is expected that the reference optimizations should perform a higher number of simulations and be more robust.

The results for the two robustness strategies are summarized below (the full results can be found in Appendix B):

Table 11: Summary Robustness and Efficiency Results Across All Optimizations, Robustness Strategies

	Num. of Simulations	Reduction in Simulations (%)	Avg. Deviation (%)	Max. Deviation (%)
Large Optimizations				
Ref.	2133	--	--	--
1	1695	20	0.12	1.72
2	1240	41	0.76	4.06
Medium Optimizations				
Ref.	273	--	--	--
1	241	11	0.19	1.89
2	174	36	0.86	5.13
Small Optimizations				
Ref.	58	--	--	--
1	52	9	0.20	1.14
2	39	31	0.37	3.53

Although there are significant simulation gains associated with the two robustness strategies, there are also maximum deviations of 1%-5%. When comparing these results to the results for the efficiency strategies (Section 6.4), we'll find that it makes little sense to deactivate either of these robustness strategies, as there are more effective ways to reduce the number of required simulations while preserving the robustness of the search (mainly through adding efficiency strategies on top of the robustness strategies in place).

Overall Robustness -- Validation

Optimization search strategies, by their nature, can never guarantee the best answer(s). Short of doing exhaustive enumeration, accuracy may be compromised for the purpose of speed increase in optimization methodologies. However, it is possible to perform validation and achieve a level of confidence about a given optimization strategy.

Ideally one would run an optimization and compare the results to those from an exhaustive parametric run. Unfortunately the time required to execute such a parametric run is prohibitive. For example, based on how long DOE-2 and TRNSYS simulations take to run, running every possible combination of 100 building efficiency options distributed unevenly across 20 categories would result in roughly 10 trillion simulations, or hundreds of years-worth of computing time on a Pentium 4 computer. Because simulations are modularized (see Section 5.1.1), the number of simulations required drops to about 10 billion.

In order to further reduce the time requirement, a distributed computing network was employed using the Condor software by the University of Wisconsin. Condor can take advantage of idle machines to run user-submitted jobs. The number of computers on our specific Condor network varied between 40 and 50. However some of the machines were slow and having to transfer large files across the network reduced the theoretical benefit of using Condor. All told, the reduction in runtime was roughly half the number of available computers on the network, or a factor of 25. The runtime requirement for an exhaustive enumeration parametric would still be several years.

Therefore, performing a large parametric run, but not an exhaustive one, remains the only practical solution. Seventy-five options were selected in order to require about 750,000 simulations, or 4 or 5 days of computer processing via the Condor network. Additional smaller validations were also performed.

In order to deal with the vast amount of data generated, information had to be filtered. Points were filtered into a bitmap where each pixel of the graph received an on/off state to represent all points found within that x- and y-coordinate box. Figure 23 illustrates one of the subsequent graphs obtained from this method for a case in Memphis[12].

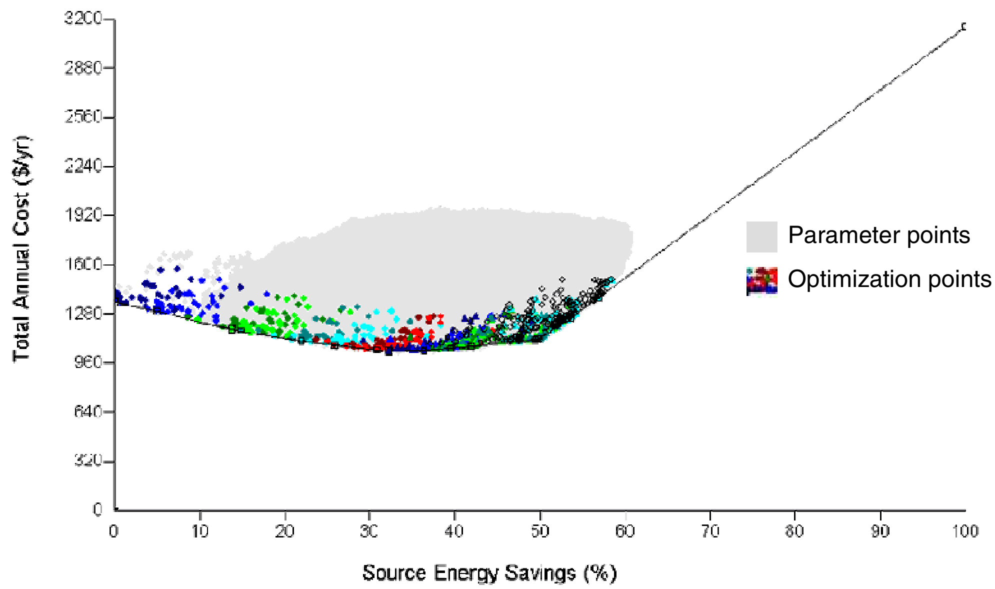

Figure 23: Validation of an Optimization, Superimposed on an Extensive Parametric

By overlaying a standard optimization graph on top of the parametric results, one can quickly gauge if parametric points fall below the optimization's lower boundary. From visual inspection, the results provide a high level of confidence that the optimization technique identifies optimal points within 1%, in terms of total annual cost, of the true lower boundary of the universe of building designs.

[12] While information was filtered into a pixel width by pixel height bitmap, the actual point representation in the graph is larger than a pixel. This is due to limitations in the graphics software.

6.4 Efficiency

6.4.1 Strategies Evaluated

Strategy 1 was included in the reference optimizations and all of the optimization strategies since *BE*opt already employs modularized simulations in order to take advantage of both DOE-2 and TRNSYS capabilities.

The remaining efficiency strategies evaluated were restricted to those that employ the same methodology across the entire optimization. While a number of strategies can be devised where the user specifies a target range of energy savings or starting point in order to reduce simulations in areas of little interest to the user, they were not considered in this research. Therefore none of the strategies involve reactive searching, or adapting the optimization parameters during the process.

Table 12 presents the complete listing of efficiency strategies, including variants, and indicates those that were evaluated with a white background (those in dark grey were not evaluated). In total, twenty variants were evaluated, spanning nine unique strategies.

Table 12: Complete Listing of Efficiency Strategies, Including Variants

	Strategy	Variant
Reducing Simulations Per Iteration		
1	Modularized simulations[1]	Base
2a	Skip superseded options	Base
2b		Simulate last superseded option
2c		Apply to well-ordered categories
3a	Skip less efficient options	Base
3b		Simulate less efficient option
3c		Simulate random less efficient option
3d		Simulate cycled option
3e		Simulate last superseded option
4a	Skip predicted outliers	5% band tolerance
4b		3% band tolerance
4c		2% band tolerance
4d		Increased tolerance for target energy savings region
5a	Mathematically filter points	Base
5b		Linear relationship between energy savings and HVAC downsizing cost savings
5c		Independent calculation of HVAC size
6a	Skip fine options	Base
6b		Cross-category application
7a	Skip extraneous points	Apply to UA categories
7b		Apply to well-ordered categories
8a	Simulate best ranked option	Apply to UA categories
8b		Apply to well-ordered categories
8c		Simulate next two best ranked options
8d		Simulate next and previous best ranked options
Reducing Iterations		
9a	Option lumping	5% cumulative energy savings, infinite non-tiny points
9b		10% cumulative energy savings, infinite non-tiny points
9c		5% cumulative energy savings, include large point, always lump tiny points, 2 non-tiny points max
9d		5% cumulative energy savings, include large point, always lump tiny points, 3 non-tiny points max
9e		5% cumulative energy savings, include large point, always lump tiny points, infinite non-tiny points
10	Forward progression	Base
11	Build up simulations	Base

Note: Strategies in gray were not evaluated

[1] Strategy 1 is included in both the reference and the efficiency optimizations.

6.4.2 Results

Figure 24 shows the twenty efficiency strategy variants along the x-axis, labeled according to the previous table. (The complete data in tabular form can be found in the Appendix C.) For each optimization, the top graph displays efficiency gains while the middle and bottom graphs display the maximum and average deviations, respectively. For each strategy, the three lines represent the span of small, medium, and large-sized optimizations; each small mark on the line represents a specific climate. Additionally, the efficiency graph contains white diamonds to mark the average of the six climates for each group of optimization sizes.

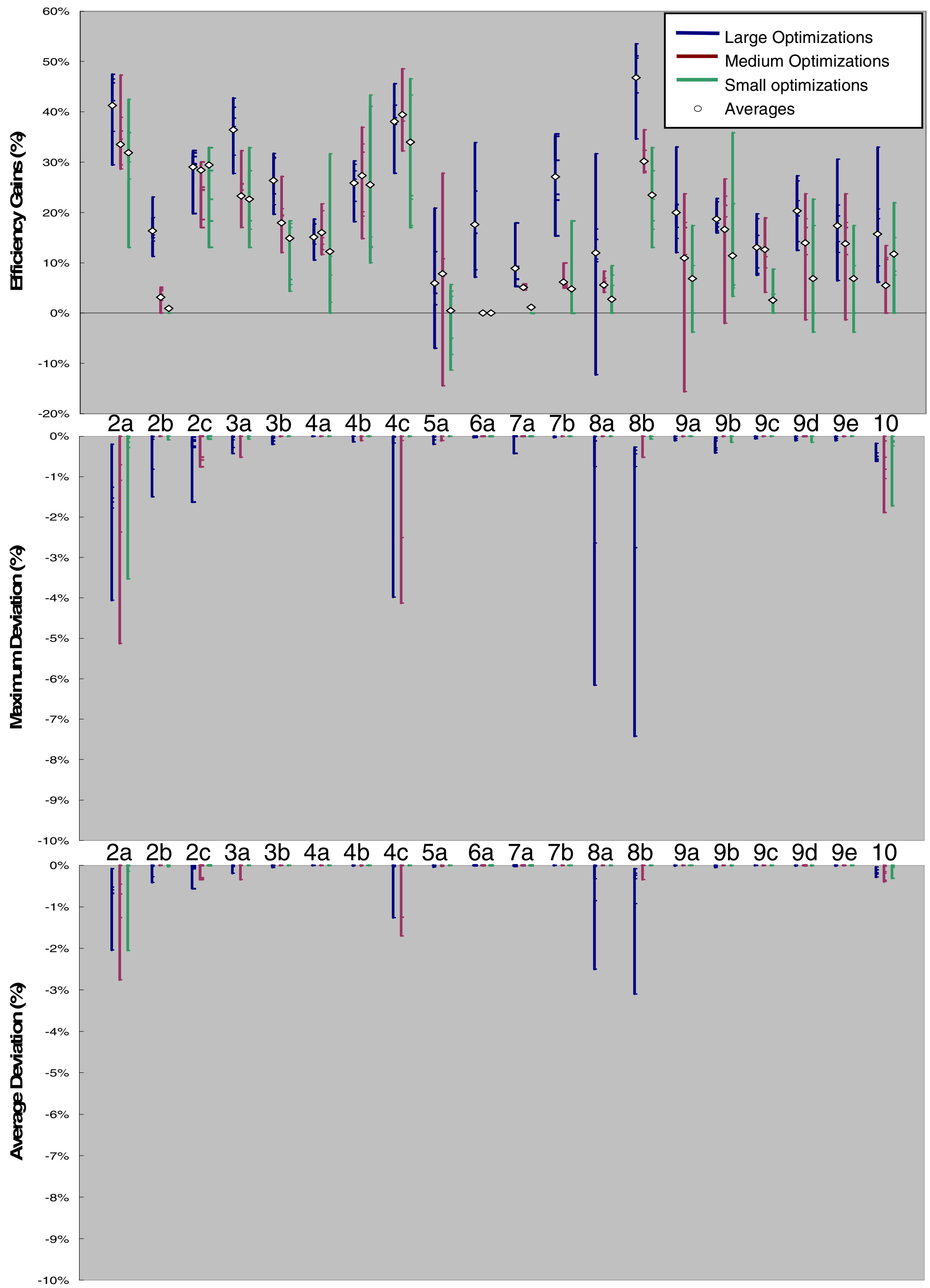

Figure 24: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies

Generally speaking, those strategies that provided the greatest efficiency gains (about 30-50% gains for strategies 2a, 4c, and 8b) also incurred the largest penalty on robustness (roughly 2% average deviation). Within each efficiency strategy, however, the six large optimizations tend to have greater efficiency gains than the medium and small optimizations. Since a percentage point of savings for a large optimization results in a greater number of absolute saved simulations then the same percentage point for a smaller optimization, the results coincide nicely with a typical user's desires (i.e. a user cares more about reaching high efficiency gains on a 10-hour optimization than a 10-minute optimization).

Additionally, there is a noticeable similarity between the average and maximum deviation graphs for each strategy. For many strategies, this is due to the PV range of the optimization curve. If the maximum deviation occurs over the PV range, as illustrated in Figure 22, and the PV range accounts for one-third of the total x-axis range, then the average deviation would tend to be at least one-third of the maximum deviation. Indeed, the average deviations tend to have 1/3 to 1/2 the value of the maximum deviations. These similarities would dissolve if multiple points were not chosen along the PV range, but then the average deviation values would not be an accurate representation of the difference between the efficiency and reference optimizations. Moreover, the average deviations will not end up being used for further analysis (see Section 6.5.1).

In addition to the quantitative results that each strategy yields, there are numerous qualitative considerations that need to be taken into account. For example, some of the efficiency gain values are highly sensitive to the specific inputs used in the test suite – the gains could span anywhere from 0% to a much larger gain than was actually seen. Also, some of the strategies impact the type of building designs that will be offered to the user (e.g. only building designs with higher capital costs), or require extra flagging/characterization in order for the strategy to be implemented. These considerations are summarized in Table 12.

Table 13: Qualitative Considerations for Evaluated Efficiency Strategies

Strategy	Limited diversity of options	Sensitive to selected options and/or costs	Requires pre-flagging categories	Other considerations
2a	Yes			
2b	Yes			
2c	Yes		Yes	
3a	Yes		Yes	
3b	Yes		Yes	
5a				- Risky for optimizations with coarse search space - Each saved simulation provides less runtime savings than other strategies
6a		Yes	Yes	
7a		Yes	Yes	
7b		Yes	Yes	
8a	Yes		Yes	
8b	Yes		Yes	
9b				- May introduce avoidable gaps (lack of points over a range of energy savings)

6.5 Packages

Having obtained results for individual robustness and efficiency strategies, the next step is to develop a set of packages: robust, conservative, moderate, and aggressive. Each subsequent package should provide increased efficiency savings while sacrificing additional robustness.

6.5.1 Distilling Results

In developing efficiency packages, it is useful to distill the vast amount of data for efficiency strategies into more basic quantities. The ultimate goal of efficiency strategies entails reducing the total runtime (i.e. total number of simulations) of all optimizations performed across all use cases – that is, across all potential users and their specific optimizations (e.g. size of search space). However, the number of saved simulations for a strategy depends on the specific percentage of large, medium, and small optimizations that are to be performed. A different set of packages would be developed for a user only interested in small optimizations versus a user only interested in large optimizations.

Figure 25 shows total efficiency gains for each strategy and for three use profile assumptions. The three use profile assumptions are:

1. 33% of the optimizations are large, 33% medium, and 33% small (33/33/33)
2. 50% of the optimizations are large, 35% medium, and 15% small (50/35/15)
3. 50% of the optimizations are large, 50% medium, and 0% small (50/50/0)

Additionally, the chart illustrates the contribution of large, medium, and small optimizations to the total efficiency.

The efficiency gains for a given use profile and strategy is calculated as

$$Efficiency\ (\%) = \frac{F_L(N_{L,R} - N_{L,E}) + F_M(N_{M,R} - N_{M,E}) + F_S(N_{S,R} - N_{S,E})}{F_L N_{L,R} + F_M N_{M,R} + \cdot F_S N_{S,R}},$$

where F_L, F_M, and F_S are the percent of large, medium, and small optimizations of the total, $N_{L,R}$, $N_{M,R}$, and $N_{S,R}$ are the number of simulations for large, medium, and small optimizations in the reference optimizations, and $N_{L,E}$, $N_{M,E}$, and $N_{S,E}$ are the number of simulations for large, medium, and small optimizations in the efficiency optimizations.

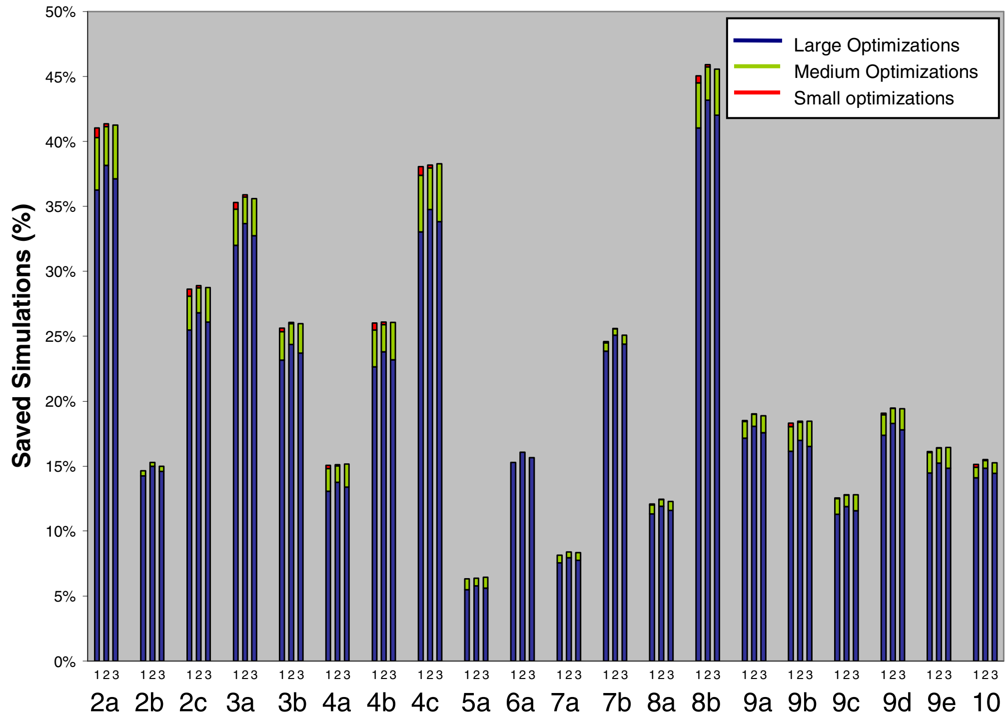

Figure 25: Number of Saved Simulations for Three Use Profiles Based on Varying Percentages of Large, Medium, and Small Optimizations: 1) 33/33/33, 2) 50/35/15, 3) 50/50/0

As one would expect, large optimizations contribute the majority of saved simulations (typically about 90-95%) with medium optimizations typically accounting for the remainder. More importantly, the contributions by large, medium, and small optimizations remains relatively constant across the three use profiles for any given efficiency strategy – in other words, the ratio of contributions are quite insensitive to the use profile assumed.

For this reason, we can confidently choose a single use profile assumption to approximate the typical sets of optimizations users will perform. This allows the eighteen climate/size optimizations for each efficiency strategy to be condensed into a single percentage value representing the total runtime savings of a strategy for typical users.

Figure 26 displays these efficiency gains, based on the 33/33/33 use profile assumption, for each strategy as white points on top of the full range of efficiency gains for each optimization.

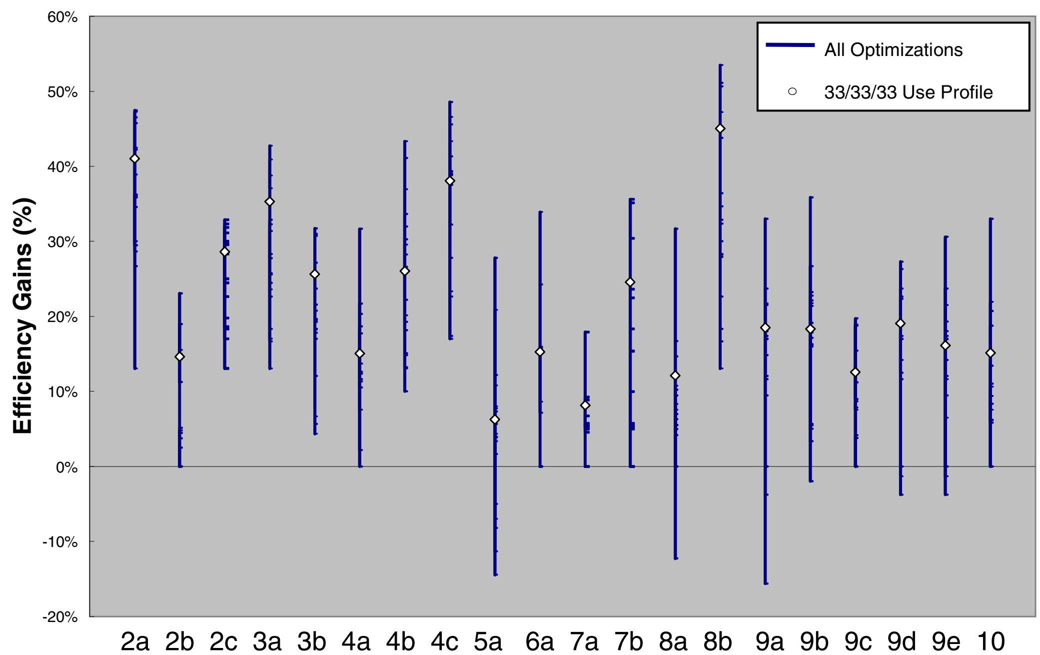

Figure 26: Single Efficiency Gain Value for 33/33/33 Use Profile

On the robustness side, average deviation for optimizations tends to be a very small value – in fact, 14 of the 17 strategies have average deviations across all optimizations of less than 0.15%. These small values typically do not rise to a level of concern, especially in light of the more critical peaks characterized by maximum deviations. Therefore, average deviation values were dropped in lieu of using the more significant maximum deviation values.

6.5.2 Selection

Having settled on the appropriate metrics for efficiency gains and robustness, a selection process for efficiency packages was devised. First, all efficiency strategies that incur a maximum deviation of greater than 1% were filtered from consideration. The remaining strategies (3a, 3b, 4a, 4b, 6a, 7b, and 9a) are then plotted on a graph of maximum deviation versus efficiency gains (see Figure 27), based on the 33/33/33 use profile. All possible combinations (packages) of these strategies[13] are included as well, where their predicted values for maximum deviations and efficiency gains are calculated by summing the individual values for each strategy. For example, the combination of strategies 4b (14.9% efficiency gain, 0.08% max deviation) and 3a (34.5% efficiency gain, 0.34% max deviation) would have predicted values of 49.4% for efficiency gains and 0.34% for maximum deviation, respectively. The points are grouped by the number of efficiency strategies integrated into the package.

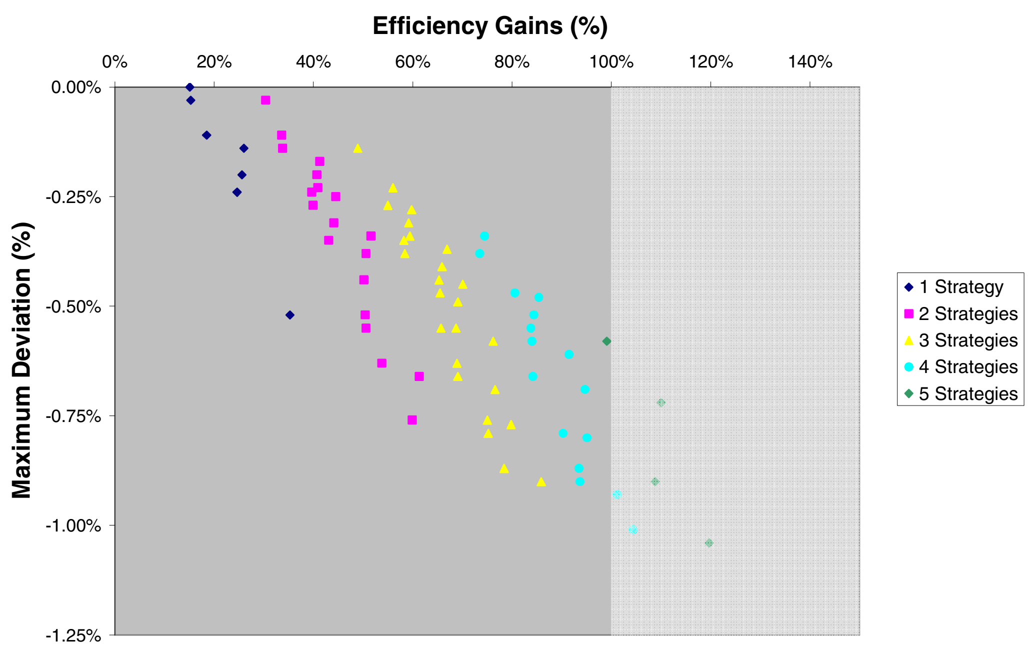

Figure 27: Predicted Efficiency Gains and Maximum Deviations for Packages Using 33/33/33 Use Profile

[13] Each combination can only include one variant of a strategy (i.e. variants, by definition, must be mutually exclusive).

The actual results, in terms of maximum deviation and efficiency gains, for each point (package) will likely differ significantly from its predicted values, and these differences will be unique to the specific strategies incorporated in the package. For example, one would expect the predicted values to over-predict efficiency gains when multiple efficiency strategies are coupled together in a package. Physically, these negative interactions for efficiency can reflect two efficiency strategies that both individually skip a specific building simulation but whose combination will only skip that building simulation once. Negative interactions are expected to increase as more efficiency strategies are coupled together.

On the other hand, the impact on maximum deviation from having multiple coupled strategies is more difficult to predict. It's possible that the maximum deviation for packages will have positive interactions, such that the combination has a maximum deviation greater than the sum of the individual strategies - but there is also the issue of coincidence of peaks. The maximum deviation value for a given strategy represents the peak at a single energy savings level of a single optimization in the test suite. Simply adding the maximum deviation values for two strategies in order to obtain a prediction would suggest that the two peaks coincide perfectly, an unlikely outcome.

The uncertainty about interactions between efficiency strategies makes it extremely difficult to predict the actual optimal efficiency packages. Therefore, as a simple approach, points A through G in Figure 28 (the front of the predicted universe of points) were selected as packages of interest. These packages represent the optimal efficiency packages, sans interactions between strategies, in terms of maximizing both efficiency gains and robustness. Given the unpredictability of how the packages' efficiency and robustness values will shift relative to their predicted values, it is conceivable that the selected packages are not the true optimal packages. However, the only way to know for certain is to run each of the packages in Figure 28 through the test suite. Unfortunately, there is a prohibitively large amount of time and effort required in implementing all packages (not to mention the additional time required for the actual running of optimizations).

The selected packages also have the benefit of providing a sequence of strategies where each package differs by one efficiency strategy, or variant, from its predecessor. This sequence has a greater likelihood of producing positive incremental efficiency gains with each package advance (from A to G) for a given optimization; if a package differed highly from its predecessor (say Package B has strategies 3a, 6a, and 7b and Package C has strategies 2a, 4a, and 10), there would be greater variability and greater possibility for regression in incremental efficiency gains.

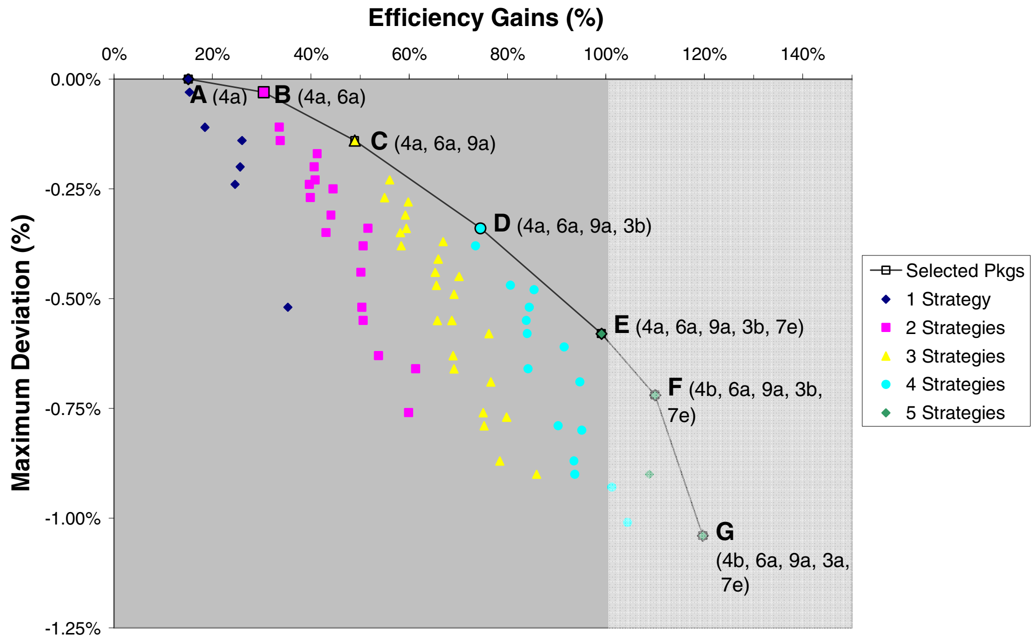

Figure 28: Selected Packages Based on Predicted Efficiency Gains and Maximum Deviations

Similar graphs to Figure 28 for each climate can be found in Figures D-1 through D-6. The figures show the predicted efficiency gains and maximum deviations for Packages A-G for a given climate's optimization results, with the large, medium, and small optimizations aggregated using the 33/33/33 use profile. If Figures D-1 through D-6 were populated with all combinations of efficiency strategies for a particular climate's optimization results, Packages A-G would likely not represent the front of the cloud of points; rather, each climate would have its own series of optimal selected packages based on predictions. Since it's improbable that efficiency packages would be offered in *BE*opt on a per-climate or per-region basis, this level of detailed analysis is not of particular interest.

While predicted efficiency gains for a given package can exceed 100%, as seen in Figure 28, actual efficiency gains cannot. In fact, the maximum achievable efficiency gain is less than 100% if one assumes that the optimal efficiency strategy is similar to the Simple Predicted-Resimulated method described in Section 3.4, which requires: A) an initial iteration's worth of simulations for each efficiency measure, in order to obtain cost and energy savings information for each measure, and B) a single simulation when each efficiency measure is introduced into the optimal building design as to account for interactions and produce actual energy savings (another full iteration of simulations, if we assume that every measure is introduced into the building at some point).

Assuming that the minimum requirement is therefore two full iterations worth of simulations for each optimization, the maximum achievable efficiency gains can be calculated for the reference optimizations of the test suite. These values are provided in Table 14. Across the six climates, it's very apparent that achievable efficiency gains decrease significantly as one reduces the size of the optimizations (this helps explain why Figure 25 demonstrated larger efficiency gains for large optimizations than for medium and small optimizations). This effect is due to the respective parameter search space for each optimization size. Because more building options comprise large optimizations compared with smaller optimizations, large optimizations tend to produce more optimal building designs, and hence, sequential search iterations. Since the maximum achievable efficiency gain is roughly[14] calculated as 100% - (2/N)*100, where N is the number of iterations in an optimization, large optimizations will have a much higher maximum value than small optimizations.

[14] Because of modularized simulations and the ability to reuse existing simulation outputs as available, one must use number of simulations, not number of iterations, to calculate the precise maximum achievable efficiency gain.

Table 14: Maximum Achievable Efficiency Gains for Each Optimization Assuming Simple Predicted-Resimulated Strategy

Maximum Achievable Efficiency Gains (%)			
	Large Optimizations	Medium Optimizations	Small Optimizations
Phoenix	93	83	67
Houston	92	81	57
Atlanta	94	85	73
San Francisco	94	81	67
Boulder	94	83	62
Chicago	93	85	62
Average	**93**	**83**	**64**

By applying the 33/33/33 use profile to values, a single representative maximum achievable efficiency gain of 91.7% can be calculated. This value expresses the maximum limit of efficiency gains that any package, using the 33/33/33 use profile, can achieve.

6.5.3 Results

Packages A through G were run put through the test suite in order to determine actual impact on efficiency and robustness. Figure 29 illustrates how the simulated values compare with the earlier predicted values (Figures D-7 through D-12 show the results for the individual six climates). As expected, the efficiency gains fall short of their predicted counterparts (with the exception of Package A, which only contains a single efficiency strategy). As for robustness, the simulated maximum deviation values exceeded the predicted values.

Figure 29 also includes a second x-axis that indicates the efficiency gains as a percentage of the maximum limit for the 33/33/33 use profile. That is to say, if a package were to achieve 91.7% efficiency gains relative to the reference optimization, it effectively achieves 100% of the possible efficiency gains.

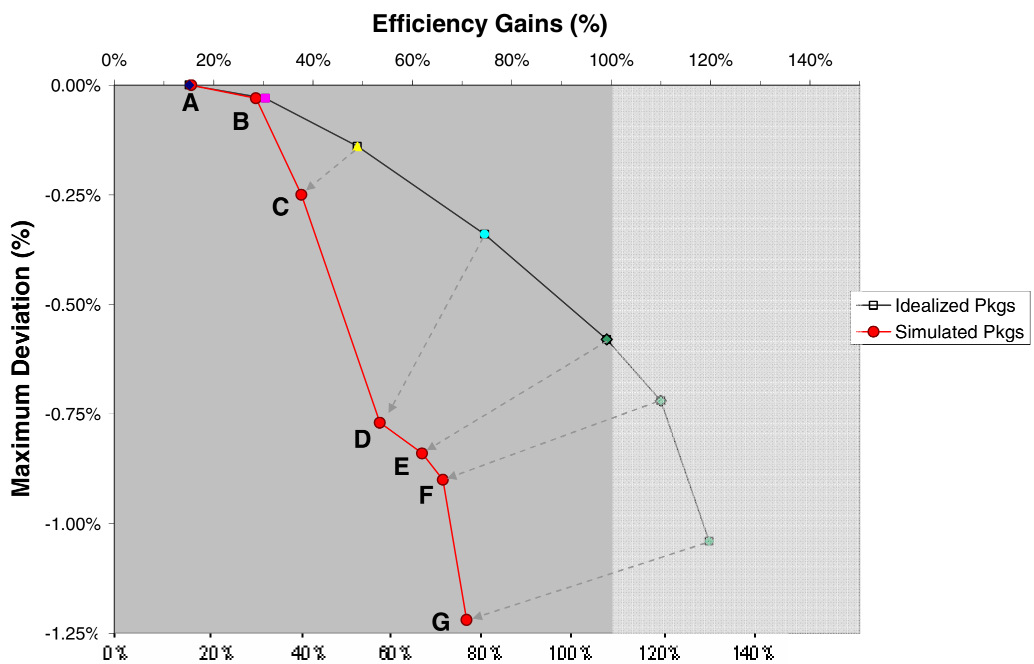

Figure 29: Simulated/Predicted Pairs for Selected Packages; 33/33/33 Use Profile

The results are also displayed in tabular form in Table 15 (Tables D-3 through D-8 likewise show the tabular results for the six climates). In addition to the 33/33/33 use profile that has been used extensively for means of analysis, the table includes the efficiency gains for large, medium, or small optimizations as well as the efficiency gains as a percentage of the maximum achievable limit. As previously noted in Figure 24, large optimizations tend to have greater efficiency gains than medium and small optimizations. Medium and small optimizations differ significantly from the 33/33/33 use profile.

Table 15: Simulated Efficiency Gains and Maximum Deviations for all Packages

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	10.2	16.7	15.5	15.5	16.9	0.00
B	10.2	16.7	30.5	28.5	31.1	0.03
C	15.6	25.3	40.0	37.6	41.0	0.25
D	26.9	42.1	55.5	53.4	58.2	0.77
E	29.7	45.7	64.8	61.9	67.5	0.84
F	38.4	54.2	68.3	66.2	72.2	0.90
G	44.0	58.4	73.0	70.9	77.3	1.22
H	45.1	64.5	78.6	76.6	83.5	6.21

Packages A through G yield increasing levels of efficiency gains with nominal gains in maximum deviation (0.03%-0.52% relative to the previous package). These packages range from conservative (15% efficiency gains, 0% maximum deviation) to aggressive (71% efficiency gains, 1.2% maximum deviation, 77% efficiency gains relative to the maximum achievable limit). Package H, the next best combination of efficiency strategies, saves another 5-6% of required simulations while its maximum deviation rises to over 6%. Figures D-13 through D-19 demonstrate the simulated efficiency gains and robustness for Packages A through G for all locations and sizes.

Figure 30 illustrates how the results of Package G (shown in red) compare with results for an optimization sans efficiency strategies (shown in grey). The multitude of red points at the onset of the optimization, on the other hand, demonstrates that all of the efficiency strategies coupled in the package still require a full iteration of simulations in order to obtain information about energy savings and cost for each efficiency measure. Most of the saved simulations come at higher energy savings where there are many possible combinations of efficiency measures that can tradeoff to achieve these levels of savings. Generally speaking, the shape of the red cloud is precisely as one would desire – the red points are in the vicinity of the lower boundary of the cloud and do not result in any avoidable energy savings ranges where there are no building designs.

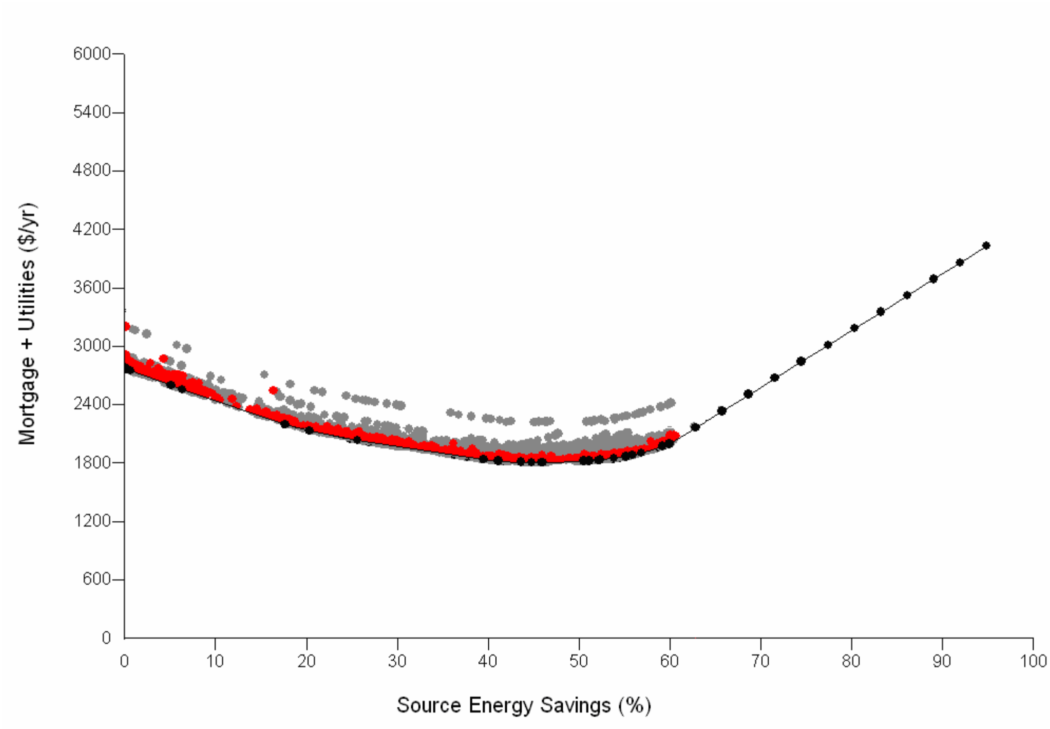

Figure 30: Package G Results (Red) Superimposed on Results for its Corresponding Reference (Grey) for Atlanta, Large Optimization

VII. CONCLUSIONS

The sequential search methodology is a particularly useful optimization strategy for identifying cost-optimal building designs over a range of energy savings levels. However, in its basic form, there are areas for potential improvement both in terms of robustness (ability to generate the true cost-optimal curve) and efficiency (number of required simulations).

Enhancements were developed to improve upon the robustness of the search by accommodating what are referred to as “invest/divest” and “large-step” special cases. Many such occurrences of both special cases were identified in optimizations using a test suite, demonstrating that more robust results were achieved. Moreover, the sequential search, with robustness strategies, was validated against a number of exhaustive enumeration parametrics and was found to yield a lower boundary within 1% of the parametrics’ lower boundary.

Additionally, various efficiency strategies were devised to reduce the total number of required simulations, by reducing the required number iterations and/or the required number of simulations per iteration. The most effective strategies at reducing total number of simulations, without significantly affecting the search’s robustness, were Strategies 4 (skip predicted outliers), 6 (skip fine points), 9 (option lumping), 3 (skip less efficient options), and 7 (skip extraneous points). Combinations of these efficiency strategies were developed into successive packages of increasing efficiency gains and risk. The packages ranged from Package A, the most conservative package that yielded 15% efficiency gains with no affect on robustness, to Package G, the most aggressive package, which couples all five individual efficiency strategies and produced 70% efficiency gains (92% maximum achievable efficiency gains) at a maximum deviation of 1.2% for the test suite.

The results presented in this document are intended to reflect typical usage of the *BE*opt software tool for optimization purposes. However, actual robustness and efficiency gains for a specific optimization will depend on a host of factors including optimization size, selected building efficiency measures, option costs, and utility rates.

VIII. FUTURE WORK

Future work could more vigorously validate the enhanced sequential search methodology against exhaustive enumeration. This would involve a very lengthy process if one is interested in gaining a high-level of confidence because of the sheer size of the parameter space, even given the potential use of a moderate-sized distributed computing network. It would also be useful to improve the resolution of the comparison and be able to retain all building descriptions for the parametric runs in order to obtain more quantifiable conclusions. Currently, Figure 23 is representative of the kind of output generated, in which the data has been distilled into a graphical display and cannot be directly accessed.

Additional strategies and strategy variants not evaluated in this document could also be implemented and analyzed (see Table 12). While a broad range of efficiency strategies were evaluated, the depth to which any given strategy could be assessed was limited. Further analysis should be performed both on the implementation side, in terms of manipulating strategies' inputs and logic via variants, and on the results side, such as comparing specific building descriptions, say at the cost-minimum point, between different strategies.

Finally, additional work is needed to better understand how the various efficiency strategies interact with each other, especially in terms of robustness. It was shown that packages of efficiency strategies perform worse, in terms of maximum deviation, than the sum of their individual strategies, but how this result is produced remains to be well understood.

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2. APPENDIX

Appendix A – Test Suite Details

Table A-1: Fixed Parameters for All Locations and Sizes

	Parameter
Geometry	2500 sqft, 2 floors, 2-car garage, 6:12 gable roof, 8 ft walls
Occupancy	3-bedrooms, 2 bathrooms
PV Cost	$7.50/W DC, 15% derate factor
Misc. Electric Loads	1.67 kWh/sqft-yr
Set Points	Const 71 deg-F heating, const 76 deg-F cooling
Mortgage	30 years, 7% nominal interest rate, 28% marginal income tax rate
Misc. Economics	30 year analysis period, 3% inflation rate, 5% nominal discount rate
Source/Site Ratio	3.16 for electric, 1.02 for gas

TableA-2: Marginal Utility Rates for All Sizes
(2005 EIA State Averages)

	Phoenix	Houston	Atlanta	San Fran	Boulder	Chicago
Electricity (c/kWh)	8.44	10.27	8.15	10.66	8.09	7.44
Natural Gas ($/therm)	1.1486	1.1524	1.6479	1.0502	0.9424	1.1134

Table A-3: Fixed Parameters for All Locations, Small Optimizations

Categories	Parameter
Orientation	North-facing
Neighbors	Left and right at 10ft
Aspect Ratio	1.33 (width/depth)
Ceiling	R-30 fiberglass
Thermal Mass	0.5 in. ceiling drywall
Window Areas	450 sqft, equal distribution
Eaves	1 ft. overhang
Refrigerator	Standard (671 kWh/yr)
Cooking Range	Gas standard (45 therms/yr)
Dishwasher	Standard
Clothes Dryer	Electric
Clothes Washer	Standard vertical axis
Plug-in Lighting	50% CFL
SDHW tilt/azimuth	South-facing, 6:12 tilt
PV tilt/azimuth	South-facing, 6:12 tilt

Table A-4: Coarse Parameter Search Space (Phoenix, Atlanta, Boulder), Small Optimizations

Categories	Parameters
Walls	R-19 batts, 2x6, 24"oc (R-14.4 Assy) R-19 batts, 2x6, 24"oc + 2" foam (R-29.9 Assy)
Infiltration	Typical (0.0005 FLA), Tightest (0.00008 FLA)
Foundation	Uninsulated slab (Phoenix and Atlanta) 15ft R10 perimeter, R5 gap slab (Phoenix and Atlanta) Uninsulated basement (Boulder) 8ft R20 exterior basement (Boulder)
Window Type	Low-e low SHGC arg (Phoenix and Atlanta) Low-e v. high SHGC arg (Phoenix and Atlanta) Low-e low SHGC (Boulder) Low-e v. high SHGC (Boulder)
Hardwired Lighting	50% CFL, 90%
Air Conditioner	SEER 13, 18
Furnace	AFUE 80%, 92.5%
Water Heater	Gas Standard (55% EF), Gas Tankless (84% EF)
Ducts	Typical (0.1 leakage frac.) (Phoenix and Atlanta) Inside (0.01 leakage frac.)
Solar DHW	No Solar DHW, 40 sqft closed loop
PV Size	0 – 6 kW (by 0.5 kWs)
Cooling Capacity	1.5 – 5.0 tons (by 0.5 tons)
Heating Capacity	30 – 150 kBtu/hr (by 10 kBtu/hr)

Table A-5: Fine Parameter Search Space (Houston, San Francisco, Chicago), Small Optimizations

Categories	Parameters
Walls	R-19 batts, 2x6, 24"oc (R-14.4 Assy) R-13 batts, 2x4, 16"oc + 1" foam (R-17.0 Assy)
Infiltration	Typical (0.0005 FLA), Tight (0.0003 FLA)
Foundation	Uninsulated slab (Houston and San Fran) 4ft R5 perimeter, R5 gap slab (Houston and San Fran) Uninsulated basement (Chicago) 4ft R10 exterior basement (Chicago)
Window Type	Low-e low SHGC arg (Houston and San Fran) Low-e v. high SHGC arg (Houston and San Fran)
Hardwired Lighting	50% CFL, 70%
Air Conditioner	SEER 13, 14
Furnace	AFUE 80%, 92.5%
Water Heater	Gas Standard (55% EF), Gas Premium (62% EF)
Ducts	Typical (0.1 leakage frac.) (Houston and San Fran) Improved (0.023 leakage frac.) (Houston and San Fran) Inside (0.01 leakage frac.) (Chicago)
Solar DHW	No Solar DHW, 40 sqft closed loop
PV Size	0 – 6 kW (by 0.5 kWs)
Cooling Capacity	1.5 – 5.0 tons (by 0.5 tons)
Heating Capacity	30 – 150 kBtu/hr (by 10 kBtu/hr)

Table A-6: Fixed Parameters for All Locations, Medium Optimizations

Categories	Parameter
Orientation	North-facing
Neighbors	Left and right at 10ft
Aspect Ratio	1.33 (width/depth)
Thermal Mass	0.5 in. ceiling drywall
Cooking Range	Gas standard (45 therms/yr)
Clothes Dryer	Electric
SDHW tilt/azimuth	South-facing, 6:12 tilt
PV tilt/azimuth	South-facing, 6:12 tilt

Table A-7: Parameter Search Space for All Locations, Medium Optimizations

Categories	Parameters
Walls	R-19 batts, 2x6, 24"oc (R-14.4 Assy) R-13 batts, 2x4, 16"oc + 1" foam (R-17.0 Assy.) R-19 batts, 2x6, 24"oc + 2" foam (R-29.9 Assy)
Ceiling	R30 fiberglass, R60
Infiltration	Typical (0.0005 FLA), Tightest (0.00008 FLA)
Foundation	Uninsulated slab (Pho, Hou, Atl, SF) 4ft R5 perimeter, R5 gap slab (Pho, Hou, Atl, SF) 15ft R10 perimeter, R5 gap slab (Pho, Hou, Atl, SF) Uninsulated basement (Boulder and Chicago) 4ft R10 exterior basement (Boulder and Chicago) 8ft R20 exterior basement (Boulder and Chicago)
Window Areas	450 sqft, equal distribution 450 sqft, 40% south facade, 20% other facades
Window Type	Low-e low SHGC arg (Pho, Hou, Atl, SF) Low-e v. high SHGC arg (Pho, Hou, Atl, SF) Low-e low SHGC (Boulder and Chicago) Low-e v. high SHGC (Boulder and Chicago)
Refrigerator	Standard (671 kWh/yr), EnergyStar (572 kWh/yr)
Dishwasher	Standard, EnergyStar
Clothes Washer	Standard vertical axis, EnergyStar horizontal axis
Hardwired Lighting	50% CFL, 70%, 90%
Plug-in Lighting	50% CFL, 90%
Air Conditioner	SEER 13, 16, 18
Furnace	AFUE 80%, 92.5%
ERV	None, 72% effective
Water Heater	Gas Standard (55% EF), Gas Tankless (84% EF)
Ducts	Typical (0.1 leakage frac.) (Pho, Hou, Atl, SF) Inside (0.01 leakage frac.)
Solar DHW	No Solar DHW, 32 sqft ICS, 64 sqft closed loop
PV Size	0 – 6 kW (by 0.5 kWs)
Cooling Capacity	1.5 – 5.0 tons (by 0.5 tons)
Heating Capacity	30 – 150 kBtu/hr (by 10 kBtu/hr)

Table A-8: Parameter Search Space for All Locations, Large Optimizations

Categories	Parameters
Orientation	North-facing, West, South, East
Neighbors	No neighbors, Left and right at 20ft, 10ft
Aspect Ratio	1.00 (width/depth), 1.50
Walls	R-11 batts, 2x4, 16”oc (R-8.2 Assy.) R-13 batts, 2x4, 16”oc (R-9.1 Assy.) R-15 batts, 2x4, 16”oc (R-9.8 Assy.) R-21 batts, 2x6, 24”oc (R-15.3 Assy.) R-11 batts, 2x4, 16”oc + 1” foam (R-15.9 Assy.) R-19 batts, 2x6, 24”oc + 1” foam (R-22.4 Assy.) R-21 batts, 2x6, 24”oc + 1” foam (R-23.5 Assy.) R-19 batts, 2x6, 24”oc + 2” foam (R-29.9 Assy)
Ceiling	R30 fiberglass, R40, R50, R60
Thermal Mass	1/2 in. ceiling drywall 2 x 5/8 in. ceiling drywall
Infiltration	Typical (0.0005 FLA) Tight (0.0003 FLA) Tightest (0.00008 FLA)
Foundation	Uninsulated slab (Pho, Hou, Atl, SF) 2ft R5 perimeter, R5 gap slab (Pho, Hou, Atl, SF) 4ft R5 perimeter, R5 gap slab (Pho, Hou, Atl, SF) 4ft R10 perimeter, R5 gap slab (Pho, Hou, Atl, SF) 15ft R10 perimeter, R5 gap slab (Pho, Hou, Atl, SF) Uninsulated basement (Boulder and Chicago) 4ft R10 exterior basement (Boulder and Chicago) 8ft R20 exterior basement (Boulder and Chicago)
Window Areas	450 sqft, equal distribution 450 sqft, 40% south facade, 20% other facades
Window Type	Double clear Low-e low SHGC arg (Pho, Hou, Atl, SF) Low-e std SHGC arg (Pho, Hou, Atl, SF) Low-e high SHGC arg (Pho, Hou, Atl, SF) Low-e v. high SHGC arg (Pho, Hou, Atl, SF) Low-e low SHGC (Boulder and Chicago) Low-e v. high SHGC (Boulder and Chicago)
Refrigerator	Standard (671 kWh/yr), EnergyStar (572 kWh/yr)
Cooking Range	Electric standard (604 kWh/yr) Gas standard (45 therms/yr)
Dishwasher	Standard, EnergyStar
Clothes Dryer	Electric, Gas
Clothes Washer	Standard vertical axis, EnergyStar horizontal axis
Hardwired Lighting	0% CFL, 10%, 20%, 40%, 50%, 70%, 80%, 90%

Plug-in Lighting	0% CFL, 10%, 20%, 40%, 50%, 70%, 80%, 90%
Air Conditioner	SEER 13, 14, 15, 17, 18
Furnace	AFUE 80%, 92.5%
ERV	None, 72% effective
Water Heater	Gas Standard (55% EF), Premium (62% EF), Tankless (84% EF)
Ducts	Typical (0.1 leakage frac.) (Pho, Hou, Atl, SF) Improved (0.023 leakage frac.) (Pho, Hou, Atl, SF) Inside (0.01 leakage frac.)
Solar DHW	No Solar DHW, 32 sqft ICS, 64 sqft closed loop
SDHW azimuth	Southwest, South, Southeast
SDHW tilt	Latitude-15, Latitude, Latitude+15
PV Size	0 – 6 kW (by 0.5 kWs)
PV azimuth	Southwest, South, Southeast
PV tilt	Latitude-15, Latitude, Latitude+15
Cooling Capacity	1.5 – 5.0 tons (by 0.5 tons)
Heating Capacity	30 – 150 kBtu/hr (by 10 kBtu/hr)

Table A-9: DOE-2 BDL Code for Design Day HVAC sizing

```
$ @HeatDesignDB, @CoolDesignDB, and @CoolDesignWB are
$ variables obtained from the location's .stat file
$ (accompanying the EPW weather file). The values in the
$ .stat files come from "Climate Design Data 2005 ASHRAE
$ Handbook.

"Heating DD" = DESIGN-DAY
   TYPE = HEATING
   DRYBULB-HIGH = @HeatDesignDB
   DRYBULB-RANGE = 0
   HOUR-HIGH = 15
   HOUR-LOW = 6
   CLOUD-AMOUNT = 10
   MONTH = 1
   NUMBER-OF-DAYS = 31
..

"Cooling DD" = DESIGN-DAY
   TYPE = COOLING
   DRYBULB-HIGH = @CoolDesignDB
   WETBULB-AT-HIGH = @CoolDesignWB
   DRYBULB-RANGE = 20
   HOUR-HIGH = 15
   HOUR-LOW = 6
   CLOUD-AMOUNT = 0
   MONTH = 7
   NUMBER-OF-DAYS = 30
..
```

Appendix B – Results for Robustness Strategies

Table B-1: Efficiency Results for All Locations and Sizes

	Number of Simulations							Reduction in Simulations (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	2047	1680	2440	2331	2305	1994	**2133**	--	--	--	--	--	--	**--**
1	1771	1521	1839	1642	1786	1608	**1695**	13	9	25	30	23	19	**20**
2	1308	1185	1305	1347	1211	1082	**1240**	36	29	47	42	47	46	**41**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	272	241	301	241	270	313	**273**	--	--	--	--	--	--	**--**
1	239	225	241	227	257	257	**241**	12	7	20	6	5	18	**11**
2	178	172	192	170	165	165	**174**	35	29	36	29	39	47	**36**
Small Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	60	46	73	60	53	53	**58**	--	--	--	--	--	--	**--**
1	51	45	57	51	58	49	**52**	15	2	22	15	-9	8	**9**
2	44	40	42	42	34	34	**39**	27	13	42	30	36	36	**31**

Table B-2: Robustness Results for All Locations and Sizes

	Average Deviation (%)							Maximum Deviation (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
1	0.25	0.00	0.31	0.05	0.08	0.01	**0.12**	0.35	0.00	1.72	0.24	0.47	0.15	**1.72**
2	0.68	0.08	2.04	0.67	0.59	0.52	**0.76**	1.63	0.20	4.06	1.78	1.26	1.53	**4.06**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
1	0.36	0.00	0.39	0.03	0.24	0.14	**0.19**	0.52	0.00	1.89	0.12	1.27	0.78	**1.89**
2	0.45	0.00	2.76	0.00	0.69	1.26	**0.86**	0.71	0.00	5.13	0.00	1.09	2.37	**5.13**
Small Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
1	0.23	0.04	0.10	0.40	0.30	0.11	**0.20**	0.54	0.18	0.41	1.14	0.88	0.56	**1.14**
2	0.00	0.00	2.05	0.01	0.14	0.01	**0.37**	0.00	0.00	3.53	0.04	0.28	0.15	**3.53**

Table B-3: Optimal Points with Special Cases Flagged for Phoenix, Large Optimization

Iter #	Option Numbers Across Categories																			# Diff.
1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	3	2	1	4	1	--
2	1	1	1	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1
3	1	1	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1
4	1	2	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1
5	1	4	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1
6	1	2	5	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	2
7	1	2	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	2
8	1	4	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	1
9	1	4	3	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	1
10	1	4	2	1	1	4	1	1	1	1	1	1	2	1	3	2	1	4	3	2
11	1	4	2	1	1	4	1	1	1	1	1	1	2	2	3	2	1	4	3	1
12	1	4	5	1	1	4	1	1	1	1	1	1	2	2	3	2	1	4	3	1
13	1	4	5	1	1	4	1	1	1	1	1	1	2	3	3	2	1	4	3	1
14	1	4	5	1	1	4	1	1	1	1	1	1	2	6	3	2	1	4	3	1
15	1	4	5	1	1	4	1	1	1	1	1	1	3	6	3	2	1	4	3	1
16	1	4	5	1	1	4	1	1	1	1	1	1	6	6	3	2	1	4	3	1
17	1	4	5	1	1	4	1	1	1	1	1	1	6	8	3	2	1	4	3	1
18	1	4	5	1	1	4	1	1	1	1	1	1	6	8	4	2	1	4	3	1
19	1	4	5	1	1	4	1	1	1	1	1	1	8	8	4	2	1	4	3	1
20	1	4	5	1	1	4	2	1	1	1	1	1	6	6	3	2	1	4	3	4
21	1	4	5	1	1	4	2	1	1	1	1	1	8	6	3	2	1	4	3	1
22	1	4	5	1	1	4	2	1	1	1	1	1	8	6	3	2	1	6	3	1
23	1	4	5	1	1	4	2	1	1	1	2	1	8	6	3	2	1	6	3	1
24	1	4	5	1	1	4	2	1	1	1	2	1	8	6	4	2	1	6	3	1
25	1	4	5	1	1	4	2	1	1	1	2	1	8	10	4	2	1	6	3	1
26	1	4	5	1	1	4	2	1	1	1	1	1	8	10	4	2	1	6	3	1
27	1	4	5	1	1	4	2	1	1	1	2	1	8	10	4	2	1	6	3	1
28	1	4	5	1	1	4	2	1	1	1	2	1	8	10	5	2	1	6	3	1
29	1	4	5	1	1	4	2	1	1	1	2	1	10	10	5	2	1	6	3	1
30	1	4	5	1	1	4	2	1	1	1	2	1	10	10	7	2	1	6	3	1
31	1	4	5	1	1	4	2	2	1	1	2	1	10	10	7	2	1	6	3	1
32	1	4	5	1	1	4	2	2	1	1	2	1	10	10	7	3	1	6	3	1
33	1	4	5	1	1	4	2	2	2	1	2	1	10	10	7	3	1	6	3	1
34	1	4	5	1	2	4	2	2	2	1	2	1	10	10	7	3	1	6	3	1
35	1	4	5	1	2	4	2	2	2	1	2	1	10	10	7	2	1	6	3	1
36	1	4	5	1	2	4	2	2	2	2	2	1	10	10	7	2	1	6	3	1
37	1	4	5	1	2	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1
38	1	4	5	1	2	4	2	2	2	2	2	2	10	10	7	3	1	6	3	1
39	1	4	5	1	4	4	2	2	2	2	2	2	10	10	7	3	1	6	3	1
40	1	4	9	1	4	4	2	2	2	2	2	2	10	10	7	3	1	6	3	1
41	1	4	9	1	4	4	2	2	2	2	2	2	10	10	7	2	1	6	3	1
42	1	4	9	1	4	3	2	2	2	2	2	2	10	10	7	2	1	6	3	1
43	1	4	9	1	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
44	1	4	8	1	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
45	1	4	8	2	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
46	1	4	5	2	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
47	1	4	8	2	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
48	1	4	10	1	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	2
49	1	4	10	2	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1
50	3	4	10	2	4	3	2	2	2	2	2	2	10	10	7	2	2	6	3	1

Invest/divest special cases   Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Table B-4: Optimal Points with Special Cases Flagged for Houston, Large Optimization

Iter #	Option Numbers Across Categories																						# Diff.
1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	--
2	1	1	2	1	1	3	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
3	1	1	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
4	4	1	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
5	1	1	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
6	1	2	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
7	1	2	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	1	6	12	1
8	1	4	2	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	1	6	12	1
9	1	4	5	1	1	4	1	1	1	1	1	1	1	1	3	2	1	4	3	1	6	12	1
10	1	4	5	1	1	4	1	1	1	1	1	1	1	3	3	2	1	4	3	1	6	12	1
11	1	4	5	1	1	4	1	1	1	1	1	1	5	3	3	2	1	4	3	1	6	12	1
12	1	4	5	1	1	4	1	1	1	1	1	1	6	3	3	2	1	4	3	1	6	12	1
13	1	4	5	1	1	4	1	1	1	1	1	1	6	2	3	2	1	4	3	1	6	12	1
14	1	4	5	1	1	4	1	1	1	1	1	1	6	6	3	2	1	4	3	1	6	12	1
15	1	4	5	1	1	4	1	1	1	1	2	1	6	6	3	2	1	4	3	1	6	12	1
16	1	4	5	1	1	4	1	1	1	1	2	1	8	6	3	2	1	4	3	1	6	12	1
17	1	4	5	1	1	4	1	1	1	1	2	1	8	8	3	2	1	4	3	1	6	12	1
18	1	4	5	1	1	4	1	1	1	1	2	1	8	10	3	2	1	4	3	1	6	12	1
19	1	4	5	1	1	4	2	1	1	1	2	1	8	10	3	2	1	4	3	1	6	12	1
20	1	4	5	1	1	4	2	1	1	1	2	1	10	10	3	2	1	4	3	1	6	12	1
21	1	4	5	1	1	4	2	1	1	1	2	1	10	10	3	2	1	6	3	1	6	12	1
22	1	4	5	1	1	4	2	1	2	1	2	1	10	10	3	2	1	6	3	1	6	12	1
23	1	4	5	1	1	4	2	1	2	1	2	1	10	10	3	3	1	6	3	1	6	12	1
24	1	4	5	1	1	4	2	1	2	1	2	1	10	10	4	3	1	6	3	1	6	12	1
25	1	4	5	1	1	4	2	1	1	1	2	1	10	10	4	3	1	6	3	1	6	12	1
26	1	4	5	1	1	4	2	1	2	1	2	1	10	10	4	3	1	6	3	1	6	12	1
27	1	4	5	1	1	4	2	1	2	1	2	1	10	10	7	3	1	6	3	1	6	12	1
28	1	4	5	1	1	4	2	2	2	1	2	1	10	10	7	3	1	6	3	1	6	12	1
29	1	4	5	1	1	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1	6	12	1
30	1	4	5	1	2	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1	6	12	1
31	3	4	5	1	2	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1	6	12	1
32	1	4	5	2	2	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1	6	12	2
33	1	4	5	2	2	4	2	2	2	2	2	1	10	10	8	3	1	6	3	1	6	12	1
34	1	4	5	1	4	4	2	2	2	2	2	1	10	10	7	3	1	6	3	1	6	12	3
35	1	4	5	1	4	4	2	2	2	2	2	1	10	10	7	3	2	6	3	1	6	12	1
36	1	4	5	1	4	4	2	2	2	2	2	2	10	10	7	3	2	6	3	1	6	12	1
37	1	4	10	1	4	4	2	2	2	2	2	2	10	10	7	3	2	6	3	1	6	12	1
38	1	4	10	1	4	3	2	2	2	2	2	2	10	10	7	3	2	6	3	1	6	12	1
39	1	4	10	2	4	3	2	2	2	2	2	2	10	10	7	3	2	6	3	1	6	12	1
40	1	4	10	2	4	3	2	2	2	2	2	2	10	10	8	3	2	6	3	1	6	12	1
41	1	4	10	2	4	3	2	2	2	2	2	2	10	10	8	3	2	6	3	2	6	12	1
42	1	4	10	2	4	3	2	2	2	2	2	2	10	10	8	3	2	6	3	2	7	12	1
43	1	4	10	2	4	3	2	2	2	2	2	2	10	10	8	3	2	6	3	2	7	13	1
44	1	4	10	2	4	3	2	2	2	2	2	2	10	10	7	3	2	6	3	2	7	13	1
45	1	4	10	1	4	3	2	2	2	2	2	2	10	10	7	3	2	6	3	2	7	13	1
46	1	4	10	2	4	3	2	2	2	2	2	2	10	10	8	3	2	6	3	2	7	13	2

Invest/divest special cases | Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Table B-5: Optimal Points with Special Cases Flagged for Atlanta, Large Optimization

Iter #	Option Numbers Across Categories																						# Diff
1	1	1	1	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	--
2	1	1	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
3	1	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
4	4	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
5	2	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	2	1	4	1	1	6	12	1
6	2	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	1	6	12	1
7	1	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	1	6	12	1
8	2	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	3	1	6	12	2
9	2	1	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	3	1	6	12	1
10	2	1	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	6	3	1	6	12	1
11	2	1	5	1	1	2	4	1	1	1	1	1	1	1	2	3	3	1	6	3	1	6	12	1
12	2	1	5	1	1	2	4	1	1	1	1	1	1	2	1	3	3	1	6	3	1	6	12	2
13	1	1	5	1	1	2	4	1	1	1	1	1	1	2	1	3	3	1	6	3	1	6	12	1
14	1	1	5	1	1	2	4	1	1	1	1	1	1	2	2	3	3	1	6	3	1	6	12	1
15	1	1	5	1	1	2	4	1	1	1	1	1	1	2	3	3	3	1	6	3	1	6	12	1
16	1	1	5	1	1	2	4	1	1	1	1	1	1	2	5	3	3	1	6	3	1	6	12	1
17	1	1	5	1	1	2	4	1	1	1	1	1	1	6	5	3	3	1	6	3	1	6	12	1
18	1	1	5	1	1	3	4	1	1	1	1	1	1	6	5	3	3	1	6	3	1	6	12	1
19	1	1	5	1	1	3	4	1	1	1	1	1	1	6	8	3	3	1	6	3	1	6	12	1
20	1	1	5	1	1	3	4	1	1	1	1	1	1	2	8	3	3	1	6	3	1	6	12	1
21	1	1	5	1	1	3	4	1	1	1	1	1	1	3	8	3	3	1	6	3	1	6	12	1
22	1	1	5	1	1	3	4	1	1	1	1	1	1	6	8	3	3	1	6	3	1	6	12	1
23	1	1	5	1	2	3	4	1	1	1	1	1	1	6	8	3	3	1	6	3	1	6	12	1
24	1	1	5	1	2	3	4	4	1	1	1	1	1	6	8	3	3	1	6	3	1	6	12	1
25	1	1	5	1	2	3	4	4	1	1	1	1	1	2	8	3	3	1	6	3	1	6	12	1
26	1	1	5	1	2	3	4	4	1	1	1	1	1	3	8	3	3	1	6	3	1	6	12	1
27	1	1	5	1	2	3	4	4	1	1	1	1	1	6	8	3	3	1	6	3	1	6	12	1
28	1	1	5	1	2	3	4	4	1	1	1	1	1	6	10	3	3	1	6	3	1	6	12	1
29	1	1	5	1	2	3	4	4	1	1	1	1	1	10	10	3	3	1	6	3	1	6	12	1
30	1	2	5	1	2	3	4	4	1	1	1	1	1	10	10	3	3	1	6	3	1	6	12	1
31	1	4	5	1	2	3	4	4	1	1	1	1	1	10	10	3	3	1	6	3	1	6	12	1
32	1	4	5	2	2	3	4	4	1	1	1	1	1	10	10	3	3	1	6	3	1	6	12	1
33	1	4	5	2	2	3	4	4	1	1	1	1	1	10	9	3	3	1	6	3	1	6	12	1
34	1	4	5	2	2	3	4	4	1	1	1	1	1	10	10	3	3	1	6	3	1	6	12	1
35	1	4	5	2	2	3	4	4	1	1	1	2	1	10	10	3	3	1	6	3	1	6	12	1
36	1	4	5	2	2	3	4	4	1	1	2	2	1	10	10	3	3	1	6	3	1	6	12	1
37	1	4	5	2	2	3	4	4	1	1	2	2	1	10	10	4	3	1	6	3	1	6	12	1
38	1	4	5	2	4	3	4	4	1	1	2	2	1	10	10	3	3	1	6	3	1	6	12	2
39	1	4	5	1	4	3	4	4	1	1	2	2	1	10	10	3	3	1	6	3	1	6	12	1
40	1	4	5	1	4	3	4	4	2	1	2	2	1	10	10	3	3	1	6	3	1	6	12	1
41	1	4	5	1	4	3	4	4	1	1	2	2	1	10	10	5	3	1	6	3	1	6	12	2
42	1	4	5	1	4	3	4	4	2	1	2	2	1	10	10	7	3	1	6	3	1	6	12	2
43	1	4	5	1	2	3	4	4	2	1	2	2	1	10	10	7	3	1	6	3	1	6	12	1
44	1	4	5	1	2	3	4	4	1	1	2	2	1	10	10	7	3	1	6	3	1	6	12	1
45	1	4	5	1	2	3	4	4	1	1	1	2	1	10	10	7	3	1	6	3	1	6	12	1
46	1	4	5	1	2	3	4	4	1	1	2	2	1	10	10	7	3	1	6	3	1	6	12	1
47	1	4	5	1	4	3	4	4	1	1	2	2	1	10	10	3	3	1	6	3	1	6	12	2
48	1	4	5	1	4	3	4	4	2	1	2	2	1	10	10	3	3	1	6	3	1	6	12	1
49	1	4	5	1	4	3	4	4	1	1	2	2	1	10	10	5	3	1	6	3	1	6	12	2
50	1	2	5	1	4	3	4	4	2	1	2	2	1	10	10	7	3	1	6	3	1	6	12	3
51	1	4	5	1	4	3	4	4	2	1	2	2	1	10	10	7	3	1	6	3	1	6	12	1
52	1	4	5	1	4	3	4	4	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
53	1	4	5	1	4	3	4	3	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
54	1	4	8	1	4	3	4	3	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
55	1	4	8	1	4	3	4	3	2	1	2	2	1	10	10	3	3	2	6	3	1	6	12	1
56	1	4	8	1	4	4	4	3	2	1	2	2	1	10	10	3	3	2	6	3	1	6	12	1
57	1	4	8	1	4	4	4	3	2	1	2	2	1	10	10	5	3	2	6	3	1	6	12	1
58	1	4	8	1	4	4	4	3	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
59	1	4	10	1	4	4	4	3	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
60	1	4	10	2	4	4	4	3	2	1	2	2	1	10	10	7	3	2	6	3	1	6	12	1
61	1	4	10	2	4	4	4	3	2	1	2	2	2	10	10	7	3	2	6	3	1	6	12	1

62	1	4	10	2	4	4	4	3	2	2	2	2	2	10	10	7	3	2	6	3	1	6	12		1
63	1	4	10	2	4	4	4	3	2	2	2	2	2	10	10	7	3	2	6	3	2	6	12		1
64	1	4	10	2	4	4	4	3	2	2	2	2	2	10	10	7	3	2	6	3	2	7	12		1
65	1	4	10	2	4	4	4	3	2	2	2	2	2	10	10	7	3	2	6	3	2	7	13		1
66	1	4	10	2	4	4	4	3	2	2	2	2	1	10	10	7	3	2	6	3	2	7	13		1
67	1	4	10	2	4	4	4	3	2	1	2	2	1	10	10	7	3	2	6	3	2	7	13		1
68	1	4	10	2	4	4	4	3	2	2	2	2	1	10	10	7	3	2	6	3	2	7	13		1
69	1	4	10	2	4	4	4	3	2	2	2	2	2	10	10	7	3	2	6	3	2	7	13		1

Invest/divest special cases Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Table B-6: Optimal Points with Special Cases Flagged for San Francisco, Large Optimization

Iter #	Option Numbers Across Categories																	# Diff
1	1	1	1	1	1	2	3	1	1	1	1	1	1	1	2	4	1	--
2	1	1	2	1	1	2	3	1	1	1	1	1	1	1	2	4	1	1
3	3	1	2	1	1	2	3	1	1	1	1	1	1	1	2	4	1	1
4	1	1	2	1	1	2	4	1	1	1	1	1	1	1	2	4	1	2
5	1	2	2	1	1	2	4	1	1	1	1	1	1	1	2	4	1	1
6	3	1	2	1	1	2	3	1	1	1	1	1	1	1	2	4	1	3
7	2	1	2	1	1	2	4	1	1	1	1	1	1	1	2	4	1	2
8	1	1	2	1	1	2	4	1	1	1	1	1	1	1	2	4	1	1
9	1	1	2	1	1	2	4	1	1	1	1	1	2	1	2	4	1	1
10	1	4	2	1	1	2	4	1	1	1	1	1	2	1	2	4	1	1
11	1	4	1	1	1	2	4	1	1	1	1	1	2	1	2	4	1	1
12	1	4	2	1	1	2	4	1	1	1	1	1	2	1	2	4	1	1
13	1	4	2	1	1	2	4	1	1	1	1	1	2	2	2	4	1	1
14	1	4	2	1	1	2	4	1	1	1	1	2	2	2	2	4	1	1
15	1	4	2	1	1	2	4	1	1	2	1	2	2	2	2	4	1	1
16	1	4	5	1	1	2	4	1	1	2	1	2	2	2	2	4	1	1
17	1	4	5	1	1	2	4	1	1	2	1	2	2	2	2	4	3	1
18	1	4	3	1	1	2	4	1	1	2	1	2	2	2	2	4	3	1
19	1	4	3	1	1	2	4	1	1	2	1	1	2	2	2	4	3	1
20	1	4	3	1	1	2	4	1	1	1	1	1	2	2	2	4	3	1
21	1	4	3	1	1	2	4	1	1	1	1	1	2	3	2	4	3	1
22	1	4	3	1	1	2	4	1	1	1	1	2	2	3	2	4	3	1
23	1	4	3	1	1	2	4	1	1	1	1	2	2	5	2	4	3	1
24	1	4	3	1	1	2	4	1	1	1	1	2	3	3	2	4	3	2
25	1	4	2	1	1	2	4	1	1	1	1	2	3	3	2	4	3	1
26	1	4	2	1	1	2	4	1	1	1	1	1	3	3	2	4	3	1
27	1	4	2	1	1	2	4	1	1	1	1	2	3	3	2	4	3	1
28	1	4	2	1	1	2	4	1	1	1	1	2	3	6	2	4	3	1
29	1	4	2	1	1	2	4	1	1	2	1	2	3	6	2	4	3	1
30	1	4	2	1	1	2	4	1	1	2	1	2	6	6	2	4	3	1
31	1	4	5	1	1	2	4	1	1	2	1	2	6	6	2	4	3	1
32	1	4	5	1	1	2	4	1	1	2	1	2	6	8	2	4	3	1
33	1	4	5	1	1	2	4	1	1	2	1	2	6	8	3	4	3	1
34	1	4	5	1	1	2	4	1	1	2	1	2	6	10	3	4	3	1
35	1	4	5	1	1	2	4	1	1	2	1	2	8	10	3	4	3	1
36	1	4	5	1	1	2	4	1	1	2	1	2	8	6	3	4	3	1
37	1	4	5	1	1	2	4	1	1	2	1	2	8	9	3	4	3	1
38	1	4	5	1	1	2	4	1	1	2	1	2	9	9	3	4	3	1
39	1	4	5	1	1	2	4	1	1	2	1	2	10	9	3	4	3	1
40	1	1	5	1	1	2	4	1	1	2	1	2	9	9	3	4	3	2
41	1	1	5	1	1	2	4	1	1	2	1	2	9	10	3	4	3	1
42	1	1	5	1	1	2	4	1	1	2	1	2	10	10	3	4	3	1
43	1	1	5	1	1	3	4	1	1	2	1	2	10	10	3	4	3	1
44	1	1	5	1	1	2	4	1	1	2	1	2	10	10	3	6	3	2
45	1	1	5	1	1	3	4	1	1	2	1	2	10	10	3	6	3	1
46	1	1	5	1	2	3	4	1	1	2	1	2	10	10	3	6	3	1
47	1	1	5	1	2	3	4	1	1	2	2	2	10	10	3	6	3	1
48	1	1	5	1	2	3	4	5	1	2	2	2	10	10	3	6	3	1
49	1	1	5	1	2	3	4	5	2	2	2	2	10	10	3	6	3	1
50	1	1	5	1	2	4	4	5	1	2	2	2	10	10	3	6	3	2
51	1	1	5	1	2	4	4	5	2	2	2	2	10	10	3	6	3	1
52	1	1	5	1	2	4	4	4	2	2	2	2	10	10	3	6	3	1
53	1	1	5	2	2	4	4	4	2	2	2	2	10	10	3	6	3	1
54	1	1	5	2	2	4	4	4	1	2	2	2	10	10	3	6	3	1
55	1	1	5	2	2	3	4	4	1	2	2	2	10	10	3	6	3	1
56	1	1	5	2	2	3	4	4	1	2	1	2	10	10	3	6	3	1
57	1	1	5	2	2	4	4	4	1	2	1	2	10	10	3	6	3	1
58	1	1	5	2	2	4	4	4	1	2	2	2	10	10	3	6	3	1
59	1	1	5	2	2	4	4	4	2	2	2	2	10	8	3	6	3	2
60	1	1	5	2	2	6	4	4	2	2	2	2	10	10	3	6	3	2
61	1	1	8	1	2	4	4	4	2	2	2	2	10	10	3	6	3	3
62	1	1	8	1	2	6	4	4	2	2	2	2	10	10	3	6	3	1
63	1	1	5	2	4	6	4	4	2	2	2	2	10	10	3	6	3	3

Invest/divest special cases   Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Table B-7: Optimal Points with Special Cases Flagged for Boulder, Large Optimization

Iter #	Option Numbers Across Categories																							# Diff
1	1	1	3	1	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	--
2	1	1	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
3	1	4	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
4	3	4	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
5	3	4	5	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
6	3	4	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
7	1	4	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
8	1	4	3	2	1	1	2	3	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
9	1	4	3	5	1	1	2	3	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
10	1	4	3	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
11	1	4	3	5	1	1	2	4	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
12	1	4	3	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
13	1	4	3	5	1	1	2	4	1	1	1	1	1	1	2	1	3	3	1	4	1	6	12	1
14	1	4	3	5	1	1	2	4	1	1	1	1	1	1	2	2	3	3	1	4	1	6	12	1
15	1	4	3	5	1	1	2	4	1	1	1	1	1	1	2	6	3	3	1	4	1	6	12	1
16	1	4	3	5	1	1	2	4	1	1	1	1	1	1	3	6	3	3	1	4	1	6	12	1
17	1	4	3	5	1	1	2	4	1	1	1	1	1	1	6	6	3	3	1	4	1	6	12	1
18	1	4	3	5	1	1	2	4	1	1	1	1	1	1	6	8	3	3	1	4	1	6	12	1
19	1	4	3	5	1	1	2	4	1	1	1	1	2	1	6	8	3	3	1	4	1	6	12	1
20	1	4	3	5	1	1	2	4	1	1	1	1	2	1	8	8	3	3	1	4	1	6	12	1
21	1	4	3	5	1	1	2	4	1	1	1	1	2	1	8	8	3	3	1	6	1	6	12	1
22	1	4	3	5	1	1	2	4	1	1	2	1	2	1	8	8	3	3	1	6	1	6	12	1
23	1	4	3	5	1	1	3	4	1	1	2	1	2	1	8	8	3	3	1	6	1	6	12	1
24	1	4	3	5	1	1	3	4	1	1	2	1	2	1	10	8	3	3	1	6	1	6	12	1
25	1	4	3	5	1	1	3	4	1	1	2	1	2	1	10	10	3	3	1	6	1	6	12	1
26	1	4	3	5	1	1	3	4	10	1	2	1	2	1	10	10	3	3	1	6	1	6	12	1
27	1	1	3	5	1	1	3	4	10	1	2	1	2	1	10	10	3	3	1	6	1	6	12	1
28	1	1	3	5	1	1	2	4	10	1	2	1	2	1	10	10	3	3	1	6	1	6	12	1
29	1	1	3	5	1	1	3	4	10	1	2	1	2	1	9	10	3	3	1	6	1	6	12	2
30	1	1	3	5	1	1	3	4	10	1	2	1	2	1	10	8	3	3	1	6	1	6	12	2
31	1	1	3	5	1	1	3	4	10	1	2	1	2	1	10	10	5	3	1	6	1	6	12	2
32	1	4	3	5	1	2	3	4	10	1	2	1	2	1	10	10	3	3	1	6	1	6	12	3
33	1	4	3	5	1	2	3	4	10	1	2	1	2	1	10	10	5	3	1	6	1	6	12	1
34	1	4	3	5	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
35	1	4	3	10	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
36	1	1	3	10	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
37	1	1	3	8	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
38	1	1	3	8	1	2	3	4	10	1	2	1	2	1	10	10	5	3	1	6	1	6	12	1
39	1	1	3	8	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
40	1	1	3	8	1	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
41	1	1	3	5	1	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
42	1	1	3	5	1	2	3	4	10	2	2	1	2	1	10	10	5	3	1	6	1	6	12	1
43	1	1	3	5	1	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
44	1	1	3	8	1	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	2
45	1	1	3	8	1	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
46	1	1	3	10	1	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
47	1	1	3	10	1	2	3	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	1
48	1	1	3	10	2	2	3	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	1
49	1	2	3	10	2	2	3	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	1
50	1	2	3	10	2	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
51	1	2	3	10	2	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
52	1	2	3	10	2	2	3	4	10	1	2	1	2	1	10	10	5	3	1	6	1	6	12	1
53	1	2	3	10	2	2	3	4	10	1	2	2	2	1	10	10	5	3	1	6	1	6	12	1
54	1	2	3	10	2	2	3	4	10	2	2	2	2	1	10	10	5	3	1	6	1	6	12	1
55	1	2	3	10	2	2	6	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	2
56	1	1	3	10	2	4	3	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	3
57	1	1	3	10	2	4	4	4	10	2	2	2	2	1	10	10	7	3	1	6	1	6	12	1
58	1	1	3	10	2	4	3	4	10	2	2	2	2	1	10	10	7	3	2	6	1	6	12	2
59	1	1	3	10	2	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
60	1	1	3	10	2	4	6	4	10	2	2	2	2	1	10	8	7	3	2	6	1	6	12	1
61	1	1	3	10	2	4	6	4	10	2	2	2	2	1	10	8	7	3	2	6	2	6	12	1
62	1	1	3	10	2	4	6	4	10	2	2	2	2	1	10	8	7	3	2	6	2	7	12	1
63	1	1	3	10	2	4	6	4	10	2	2	2	2	1	10	8	7	3	2	6	2	7	13	1
64	1	1	3	10	3	4	6	4	10	2	2	2	2	1	10	8	7	3	2	6	2	7	13	1
65	1	1	3	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	13	1
66	1	1	3	10	3	4	6	4	10	2	2	2	2	2	10	10	7	3	2	6	2	7	13	1
67	1	1	3	10	3	4	7	4	10	2	2	2	2	2	10	10	7	3	2	6	2	7	13	1
68	1	2	3	10	3	4	7	4	10	2	2	2	2	2	10	10	7	3	2	6	2	7	13	1

69	1	2	3	10	3	4	7	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	13	1
70	1	2	3	10	3	4	7	4	10	2	2	2	2	2	10	10	7	3	2	6	2	7	13	1

Invest/divest special cases Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Table B-8: Optimal Points with Special Cases Flagged for Chicago, Large Optimization

Iter #	Option Numbers Across Categories																					# Diff
1	1	1	1	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
2	1	1	2	1	1	2	3	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
3	1	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	2	1	4	1	6	12	1
4	1	1	2	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
5	1	1	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
6	1	4	5	1	1	2	4	1	1	1	1	1	1	1	1	3	3	1	4	1	6	12	1
7	1	4	5	1	1	2	4	1	1	1	1	1	1	2	1	3	3	1	4	1	6	12	1
8	1	4	5	1	1	2	4	1	1	1	1	1	1	2	3	3	3	1	4	1	6	12	1
9	1	4	5	1	1	2	4	1	1	1	1	1	1	2	3	3	3	1	6	1	6	12	1
10	1	4	5	1	1	2	4	1	1	1	1	1	1	6	3	3	3	1	6	1	6	12	1
11	1	4	5	1	1	2	4	1	1	1	1	1	1	6	5	3	3	1	6	1	6	12	1
12	1	4	5	1	1	2	4	1	1	1	1	1	1	6	8	3	3	1	6	1	6	12	1
13	1	4	5	1	1	3	4	1	1	1	1	1	1	6	8	3	3	1	6	1	6	12	1
14	1	4	5	1	1	3	4	1	1	1	1	1	1	6	6	3	3	1	6	1	6	12	2
15	1	4	5	1	1	3	4	1	1	1	1	1	1	8	8	3	3	1	6	1	6	12	1
16	1	4	5	1	1	3	4	1	1	1	1	2	1	8	8	3	3	1	6	1	6	12	1
17	1	4	5	1	2	3	4	1	1	1	1	2	1	8	8	3	3	1	6	1	6	12	1
18	1	4	5	1	2	3	4	10	1	1	1	2	1	8	8	3	3	1	6	1	6	12	1
19	1	2	5	1	2	3	4	10	1	1	1	2	1	8	8	3	3	1	6	1	6	12	1
20	1	2	5	1	2	3	4	10	1	1	1	1	1	8	8	3	3	1	6	1	6	12	1
21	1	2	5	1	2	2	4	10	1	1	1	1	1	8	8	3	3	1	6	1	6	12	1
22	1	2	5	1	2	2	4	10	1	1	1	1	1	6	8	3	3	1	6	1	6	12	1
23	1	2	5	1	2	3	4	10	1	1	1	1	1	6	8	3	3	1	6	1	6	12	1
24	1	2	5	1	2	3	4	10	1	1	1	1	1	6	10	3	3	1	6	1	6	12	1
25	1	2	5	1	2	3	4	10	1	1	1	2	1	6	10	3	3	1	6	1	6	12	1
26	1	2	5	1	2	3	4	10	1	1	1	2	1	8	10	3	3	1	6	1	6	12	2
27	1	2	5	1	2	3	4	10	1	1	1	2	1	9	8	3	3	1	6	1	6	12	1
28	1	2	5	1	2	3	4	10	1	1	1	2	1	9	9	3	3	1	6	1	6	12	1
29	1	2	8	1	2	3	4	10	1	1	1	2	1	9	9	3	3	1	6	1	6	12	1
30	1	2	8	1	2	3	4	8	1	1	1	2	1	9	9	3	3	1	6	1	6	12	1
31	1	2	8	1	2	3	4	8	1	1	1	2	1	10	9	3	3	1	6	1	6	12	1
32	1	2	10	1	2	3	4	8	1	1	1	2	1	10	9	3	3	1	6	1	6	12	1
33	1	2	10	1	2	3	4	9	1	1	1	2	1	10	9	3	3	1	6	1	6	12	1
34	1	2	10	1	2	3	4	9	1	1	1	2	1	10	10	3	3	1	6	1	6	12	1
35	1	2	10	1	4	3	4	9	1	1	1	2	1	10	10	3	3	1	6	1	6	12	1
36	1	1	10	1	4	3	4	9	1	1	1	2	1	10	10	3	3	1	6	1	6	12	1
37	1	1	10	1	4	3	4	9	1	1	1	2	1	10	8	3	3	1	6	1	6	12	2
38	1	1	10	1	4	3	4	9	1	1	1	2	1	10	10	3	3	2	6	1	6	12	1
39	1	1	10	1	4	3	4	9	1	1	2	2	1	10	10	3	3	2	6	1	6	12	1
40	1	1	10	2	4	3	4	9	1	1	2	2	1	10	10	3	3	2	6	1	6	12	1
41	1	1	10	2	4	3	4	9	1	2	2	2	1	10	10	3	3	2	6	1	6	12	1
42	1	1	10	2	4	6	4	9	1	2	2	2	1	10	10	3	3	2	6	1	6	12	1
43	1	1	10	2	4	6	4	9	2	2	2	2	1	10	10	3	3	2	6	1	6	12	1
44	1	1	10	2	4	6	4	9	2	2	2	2	1	10	10	5	3	2	6	1	6	12	1
45	1	1	10	2	4	6	4	9	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
46	1	4	10	2	4	6	4	9	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
47	1	4	10	3	4	6	4	9	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
48	1	4	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
49	1	1	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	1	6	12	1
50	1	1	10	3	4	6	4	10	2	2	2	2	2	10	10	7	3	2	6	1	6	12	2
51	1	1	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	2	6	12	1
52	1	1	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	12	1
53	1	1	10	3	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	13	1
54	1	1	10	4	4	6	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	13	1
55	1	1	10	4	4	7	4	10	2	2	2	2	1	10	10	7	3	2	6	2	7	13	1
56	1	1	10	4	4	7	4	10	2	2	2	2	2	10	10	7	3	2	6	2	7	13	1

Invest/divest special cases   Large-step special cases

Note: Only option numbers for categories where changes occurred are shown.

Appendix C – Results for Efficiency Strategies

Table C-1: Efficiency Results for All Locations and Sizes

	Number of Simulations							Reduction in Simulations (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	2047	1680	2440	2331	2305	1994	**2133**	--	--	--	--	--	--	**--**
2a	1308	1185	1305	1347	1211	1082	**1240**	36	29	47	42	47	46	**41**
2b	1754	1491	2061	1889	1961	1534	**1782**	14	11	16	19	15	23	**16**
2c	1386	1348	1663	1643	1588	1402	**1505**	32	20	32	30	31	30	**29**
3a	1405	1214	1442	1467	1320	1221	**1345**	31	28	41	37	43	39	**36**
3b	1606	1350	1690	1779	1574	1376	**1563**	22	20	31	24	32	31	**26**
4a	1663	1410	2085	1994	1885	1779	**1803**	19	16	15	14	18	11	**15**
4b	1416	1276	1713	1705	1627	1593	**1555**	31	24	30	27	29	20	**27**
4c	1428	1307	1719	1711	1654	1632	**1575**	30	22	30	27	28	18	**26**
5a	1966	1615	1931	2047	2466	1961	**1998**	4	4	21	12	-7	2	**6**
6a	1721	1560	2230	1963	1746	1318	**1756**	16	7	9	16	24	34	**18**
7a	1866	1567	2311	2116	2182	1637	**1947**	9	7	5	9	5	18	**9**
7b	1587	1422	1864	1512	1605	1284	**1546**	22	15	24	35	30	36	**27**
8a	1827	1886	2191	1942	1575	1702	**1854**	11	-12	10	17	32	15	**12**
8b	1151	1098	1288	1084	1127	984	**1122**	44	35	47	53	51	51	**47**
9a	1607	1394	1911	1985	2027	1336	**1710**	21	17	22	15	12	33	**20**
9b	1581	1412	2004	1951	1910	1553	**1735**	23	16	18	16	17	22	**19**
9c	1731	1548	2256	1894	2098	1601	**1855**	15	8	8	19	9	20	**13**
9d	1509	1356	1895	2040	1978	1450	**1705**	26	19	22	12	14	27	**20**
9e	1607	1356	2282	2000	2027	1384	**1776**	21	19	6	14	12	31	**17**
10	1855	1577	1935	1562	2162	1620	**1785**	9	6	21	33	6	19	**16**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	272	241	301	241	270	313	**273**	--	--	--	--	--	--	**--**
2a	178	172	192	170	165	165	**174**	35	29	36	29	39	47	**36**
2b	258	232	301	235	258	298	**264**	5	4	0	2	4	5	**3**
2c	204	182	245	200	204	219	**209**	25	24	19	17	24	30	**23**
3a	202	182	230	200	201	212	**205**	26	24	24	17	26	32	**25**
3b	219	191	246	212	218	228	**219**	19	21	18	12	19	27	**19**
4a	216	187	268	206	232	257	**228**	21	22	11	15	14	18	**17**
4b	186	160	247	151	225	261	**205**	32	34	18	37	17	17	**26**
4c	185	160	243	152	230	250	**203**	32	34	19	37	15	20	**26**

5a	251	215	279	174	309	288	**253**	8	11	7	28	-14	8	**8**
6a	272	241	301	241	270	313	**273**	0	0	0	0	0	0	**0**
7a	258	229	285	230	255	295	**259**	5	5	5	5	6	6	**5**
7b	258	229	285	217	255	295	**257**	5	5	5	10	6	6	**6**
8a	257	229	280	231	253	287	**256**	6	5	7	4	6	8	**6**
8b	184	163	217	173	189	199	**188**	32	32	28	28	30	36	**31**
9a	223	213	348	200	206	260	**242**	18	12	-16	17	24	17	**12**
9b	220	202	307	185	198	246	**226**	19	16	-2	23	27	21	**17**
9c	237	214	274	214	219	300	**243**	13	11	9	11	19	4	**11**
9d	221	213	305	200	206	260	**234**	19	12	-1	17	24	17	**14**
9e	223	213	305	200	206	260	**235**	18	12	-1	17	24	17	**14**
10	242	227	269	241	270	271	**253**	11	6	11	0	0	13	**7**

Small Optimizations

	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	60	46	73	60	53	53	**58**	--	--	--	--	--	--	**--**
2a	44	40	42	42	34	34	**39**	27	13	42	30	36	36	**31**
2b	60	46	73	60	53	53	**58**	0	0	0	0	0	0	**0**
2c	49	40	49	49	38	41	**44**	18	13	33	18	28	23	**22**
3a	49	40	49	50	38	41	**45**	18	13	33	17	28	23	**22**
3b	49	44	60	56	44	50	**51**	18	4	18	7	17	6	**12**
4a	43	44	64	64	45	49	**52**	28	4	12	-7	15	8	**10**
4b	41	51	41	53	45	48	**47**	32	-11	44	12	15	9	**17**
4c	34	40	43	54	46	45	**44**	43	13	41	10	13	15	**23**
5a	63	44	79	58	59	50	**59**	-5	4	-8	3	-11	6	**-2**
6a	60	46	73	60	53	53	**58**	0	0	0	0	0	0	**0**
7a	60	46	73	60	53	53	**58**	0	0	0	0	0	0	**0**
7b	60	46	73	49	53	53	**56**	0	0	0	18	0	0	**3**
8a	60	46	69	60	48	49	**55**	0	0	5	0	9	8	**4**
8b	49	40	49	50	38	41	**45**	18	13	33	17	28	23	**22**
9a	60	38	73	60	55	48	**56**	0	17	0	0	-4	9	**4**
9b	57	36	69	58	50	34	**51**	5	22	5	3	6	36	**13**
9c	60	42	73	60	51	51	**56**	0	9	0	0	4	4	**3**
9d	60	38	73	60	55	41	**55**	0	17	0	0	-4	23	**6**
9e	60	38	73	60	55	48	**56**	0	17	0	0	-4	9	**4**
10	55	46	57	51	53	49	**52**	8	0	22	15	0	8	**9**

Table C-2: Robustness Results for All Locations and Sizes

	Average Deviation (%)							Maximum Deviation (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
2a	0.68	0.08	2.04	0.67	0.59	0.52	**0.76**	1.63	0.20	4.06	1.78	1.26	1.53	**4.06**
2b	0.41	0.00	0.00	0.02	0.00	0.27	**0.12**	1.50	0.00	0.00	0.08	0.02	0.82	**1.50**
2c	0.56	0.05	0.03	0.01	0.01	0.08	**0.12**	1.63	0.12	0.28	0.02	0.09	0.25	**1.63**
3a	0.19	0.00	0.03	0.00	0.02	0.00	**0.04**	0.43	0.00	0.28	0.02	0.09	0.03	**0.43**
3b	0.01	0.00	0.00	0.05	0.00	0.00	**0.01**	0.12	0.00	0.02	0.20	0.05	0.02	**0.20**
4a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
4b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.01	0.00	0.00	0.00	**0.01**
4c	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.00	0.00	0.14	0.00	0.00	**0.14**
5a	0.00	0.00	0.00	0.00	0.00	0.04	**0.01**	0.02	0.00	0.00	0.00	0.09	0.20	**0.20**
6a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.02	0.00	0.00	0.01	0.03	0.03	**0.03**
7a	0.00	0.00	0.00	0.00	0.00	0.02	**0.00**	0.00	0.00	0.00	0.00	0.00	0.43	**0.43**
7b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.01	0.00	0.01	0.01	0.03	0.01	**0.03**
8a	0.02	0.00	0.32	0.00	2.50	0.85	**0.62**	0.12	0.0	0.75	0.00	6.16	2.64	**6.16**
8b	0.19	0.24	0.32	0.08	3.10	0.92	**0.81**	0.35	0.44	0.75	0.27	7.42	2.76	**7.42**
9a	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.06	0.00	0.11	0.01	0.01	**0.11**
9b	0.00	0.00	0.05	0.03	0.01	0.00	**0.02**	0.02	0.06	0.41	0.34	0.12	0.29	**0.41**
9c	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.06	0.02	0.00	0.00	0.01	**0.06**
9d	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.06	0.00	0.11	0.01	0.01	**0.11**
9e	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.06	0.00	0.11	0.01	0.01	**0.11**
10	0.21	0.04	0.10	0.28	0.18	0.11	**0.15**	0.50	0.18	0.41	0.62	0.59	0.56	**0.62**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
2a	0.45	0.00	2.76	0.00	0.69	1.26	**0.86**	0.71	0.00	5.13	0.00	1.09	2.37	**5.13**
2b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
2c	0.34	0.00	0.00	0.00	0.30	0.31	**0.16**	0.52	0.00	0.00	0.00	0.59	0.76	**0.76**
3a	0.34	0.00	0.00	0.00	0.00	0.00	**0.06**	0.52	0.00	0.00	0.00	0.00	0.01	**0.52**
3b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**
4a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
4b	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.00	0.00	0.11	0.00	0.00	**0.11**
4c	0.00	0.00	0.00	0.01	0.00	0.00	**0.00**	0.00	0.00	0.00	0.11	0.00	0.00	**0.11**
5a	0.00	0.00	0.02	0.01	0.00	0.00	**0.01**	0.00	0.00	0.11	0.11	0.00	0.00	**0.11**
6a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
7a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
7b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
8a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
8b	0.34	0.00	0.00	0.00	0.00	0.00	**0.06**	0.52	0.00	0.00	0.00	0.00	0.00	**0.52**
9a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**

9b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**
9c	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
9d	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**
9e	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.01	**0.01**
10	0.36	0.00	0.39	0.02	0.19	0.15	**0.19**	0.52	0.00	1.89	0.12	1.05	0.82	**1.89**
Small Optimizations													
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
2a	0.00	0.00	2.05	0.01	0.14	0.01	**0.37**	0.00	0.00	3.53	0.04	0.28	0.15	**3.53**
2b	0.00	0.00	0.00	0.00	0.00	0.03	**0.01**	0.00	0.00	0.00	0.00	0.00	0.09	**0.09**
2c	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.07	0.00	0.00	0.00	**0.07**
3a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.07	0.00	0.00	0.00	**0.07**
3b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
4a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
4b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
4c	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
5a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
6a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
7a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
7b	0.00	0.00	0.00	0.04	0.00	0.00	**0.01**	0.00	0.00	0.00	0.24	0.00	0.00	**0.24**
8a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
8b	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.07	0.00	0.00	0.00	**0.07**
9a	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
9b	0.00	0.00	0.00	0.00	0.00	0.01	**0.00**	0.00	0.00	0.00	0.00	0.00	0.15	**0.15**
9c	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
9d	0.00	0.00	0.00	0.00	0.00	0.01	**0.00**	0.00	0.00	0.00	0.00	0.00	0.15	**0.15**
9e	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
10	0.01	0.00	0.31	0.05	0.05	0.01	**0.06**	0.12	0.00	1.72	0.24	0.00	0.15	**1.72**

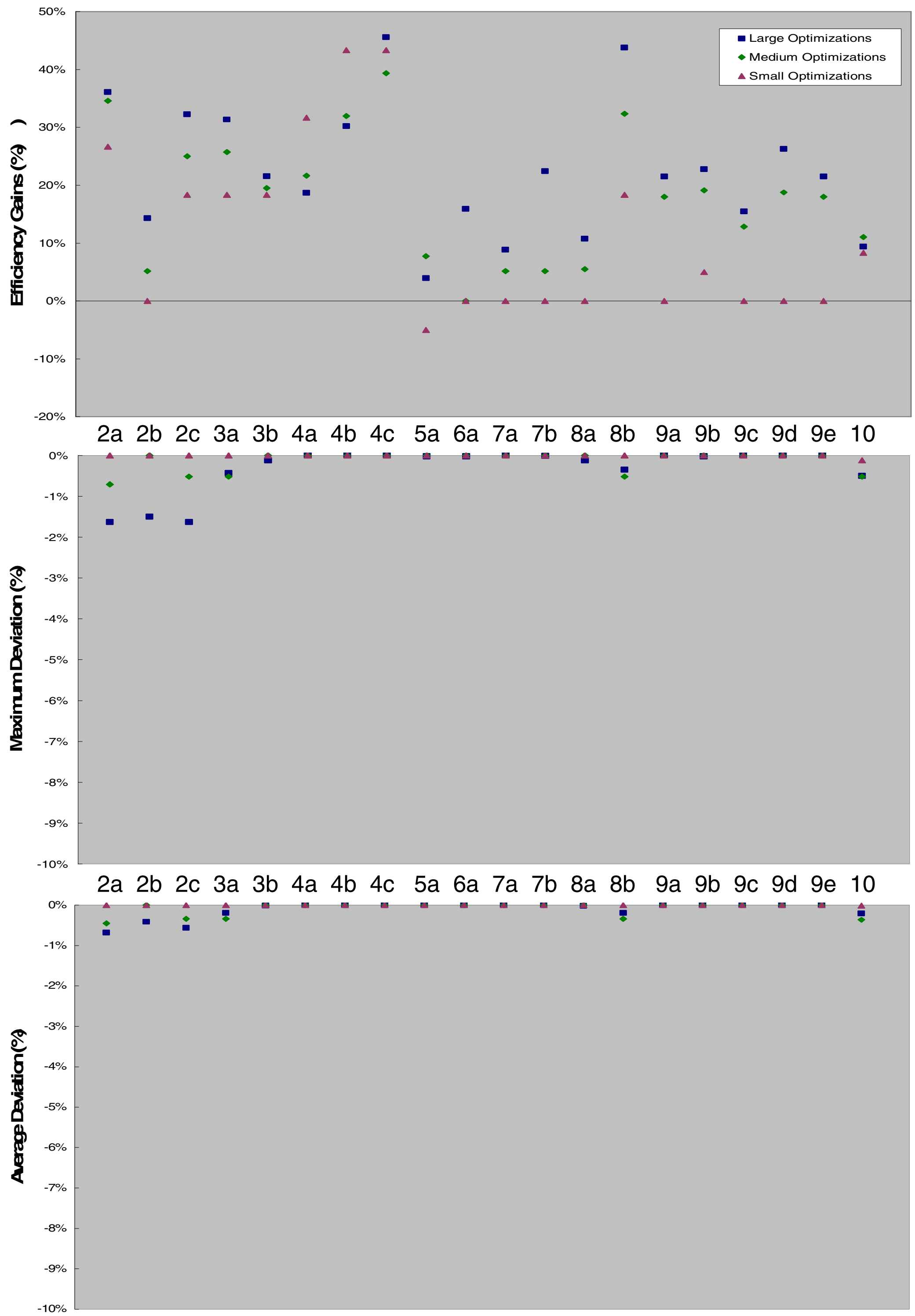

Figure C-1: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, Phoenix

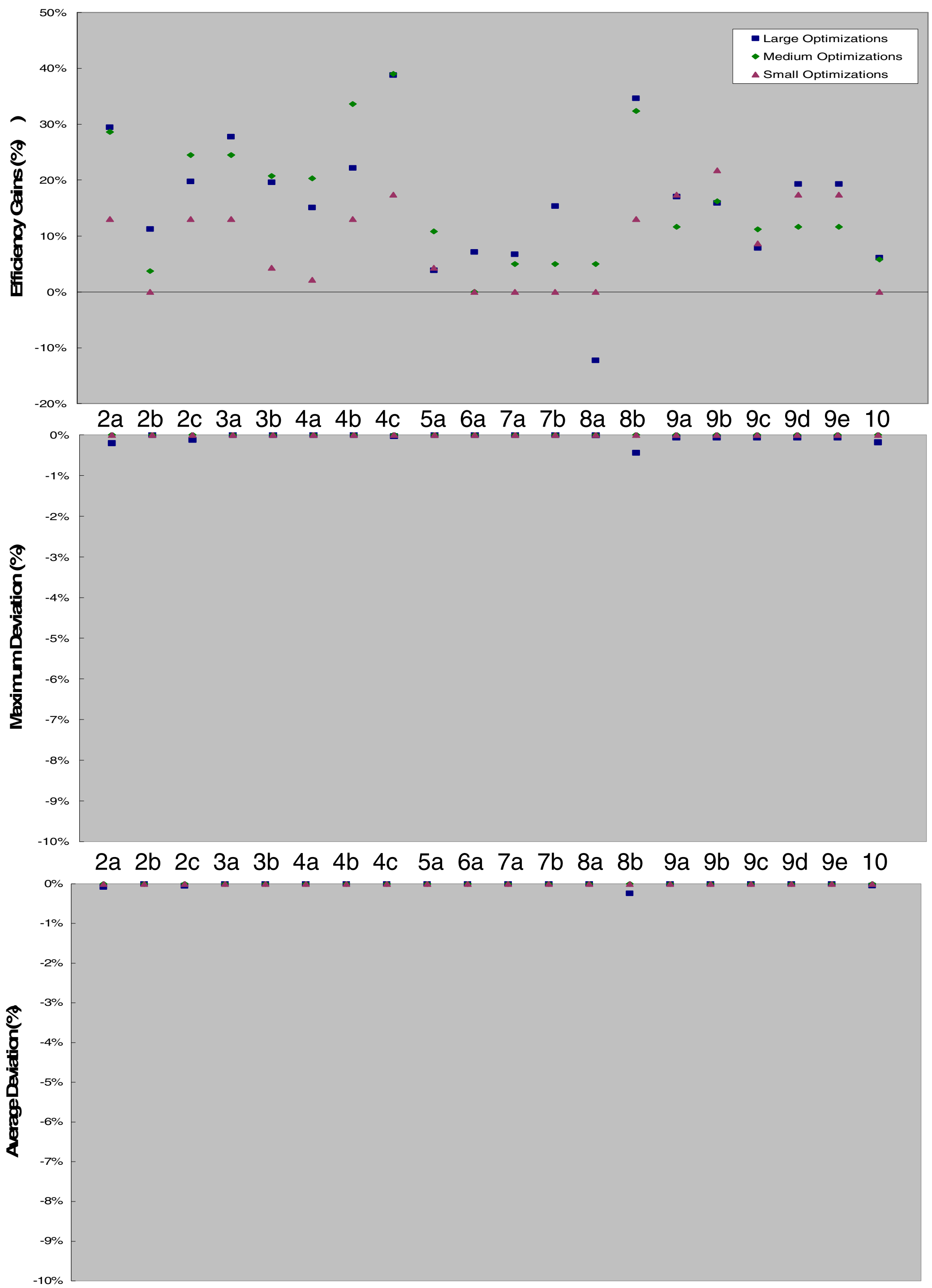

Figure C-2: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, Houston

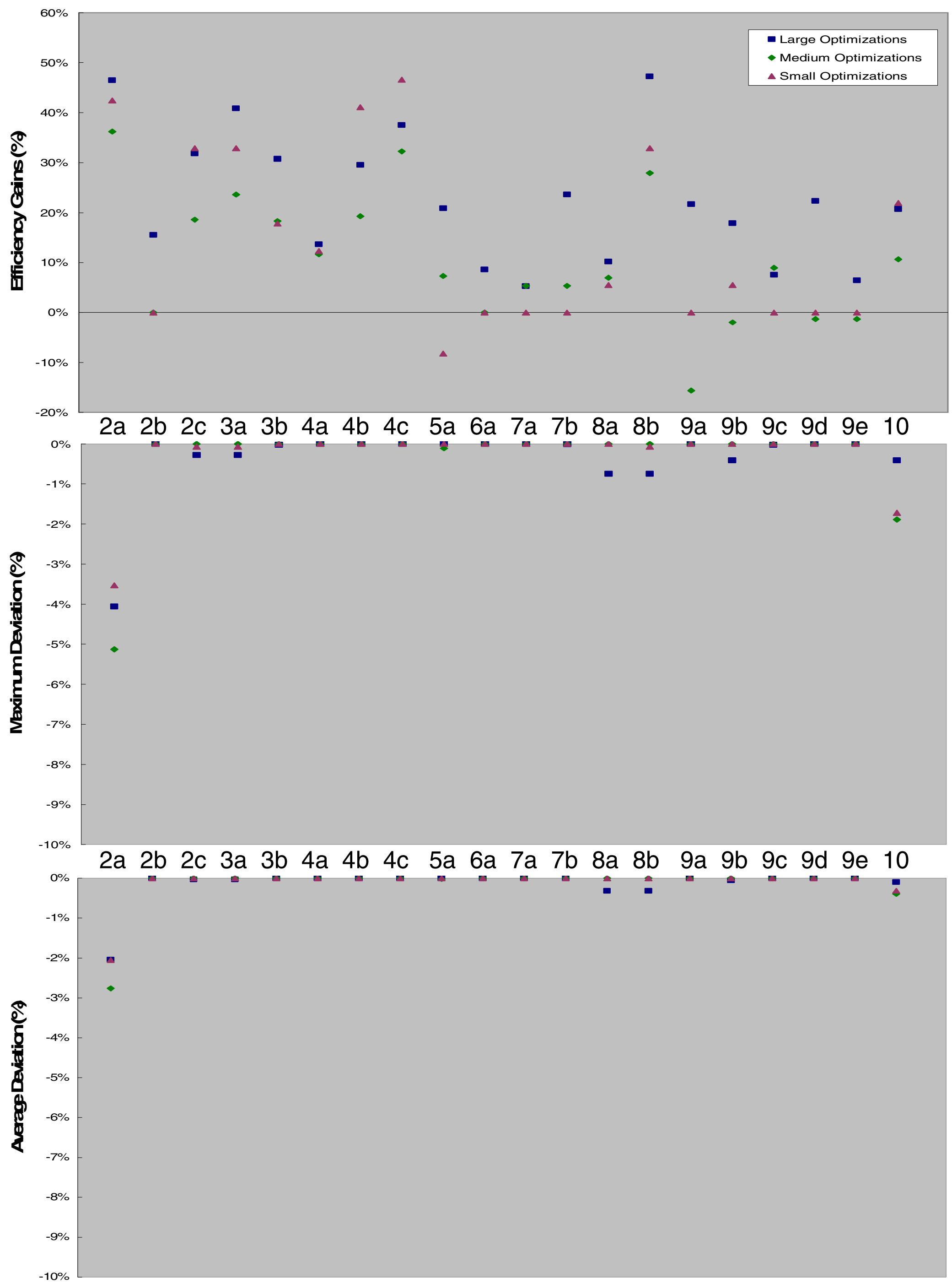

Figure C-3: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, Atlanta

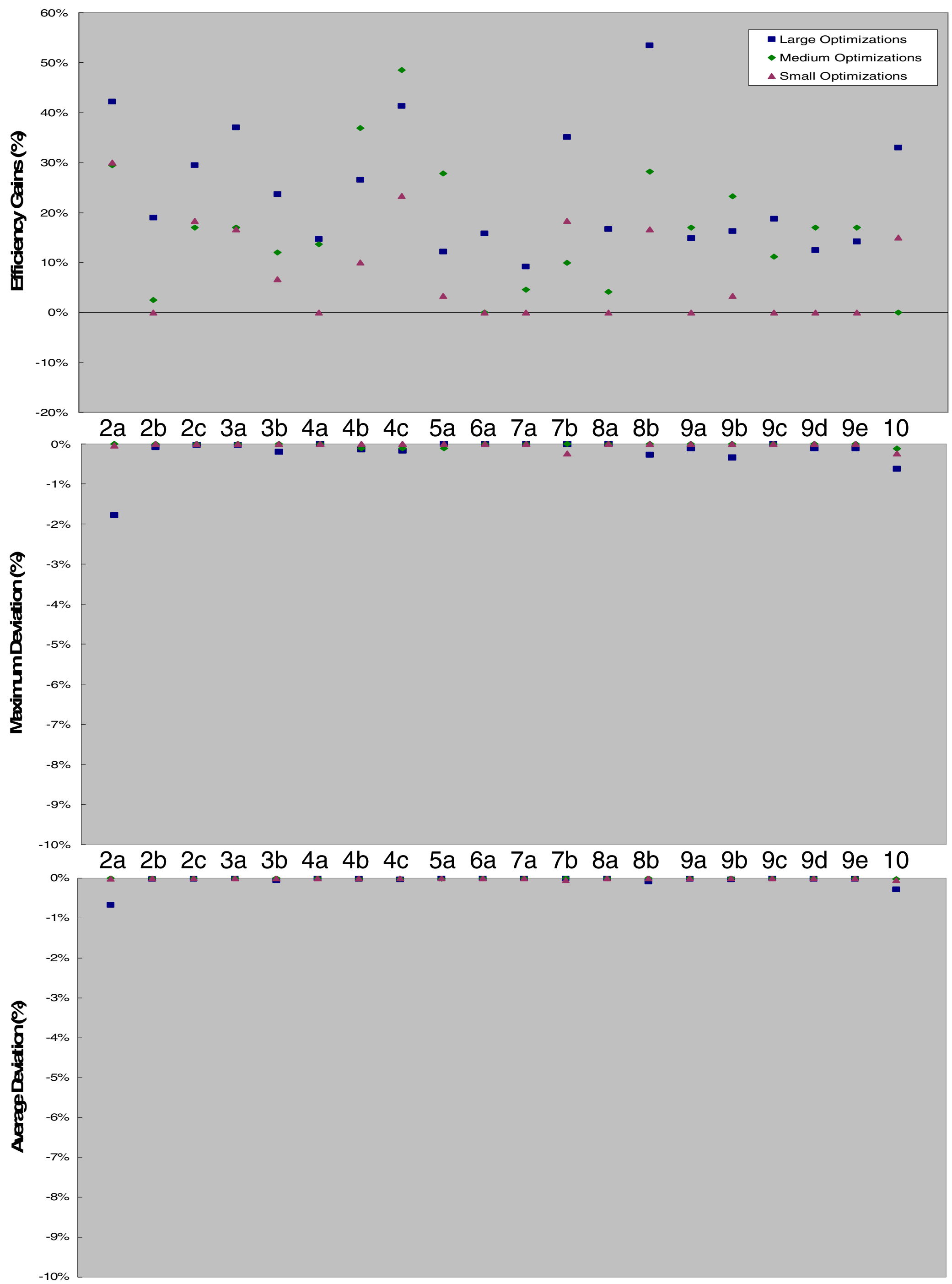

Figure C-4: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, San Fran

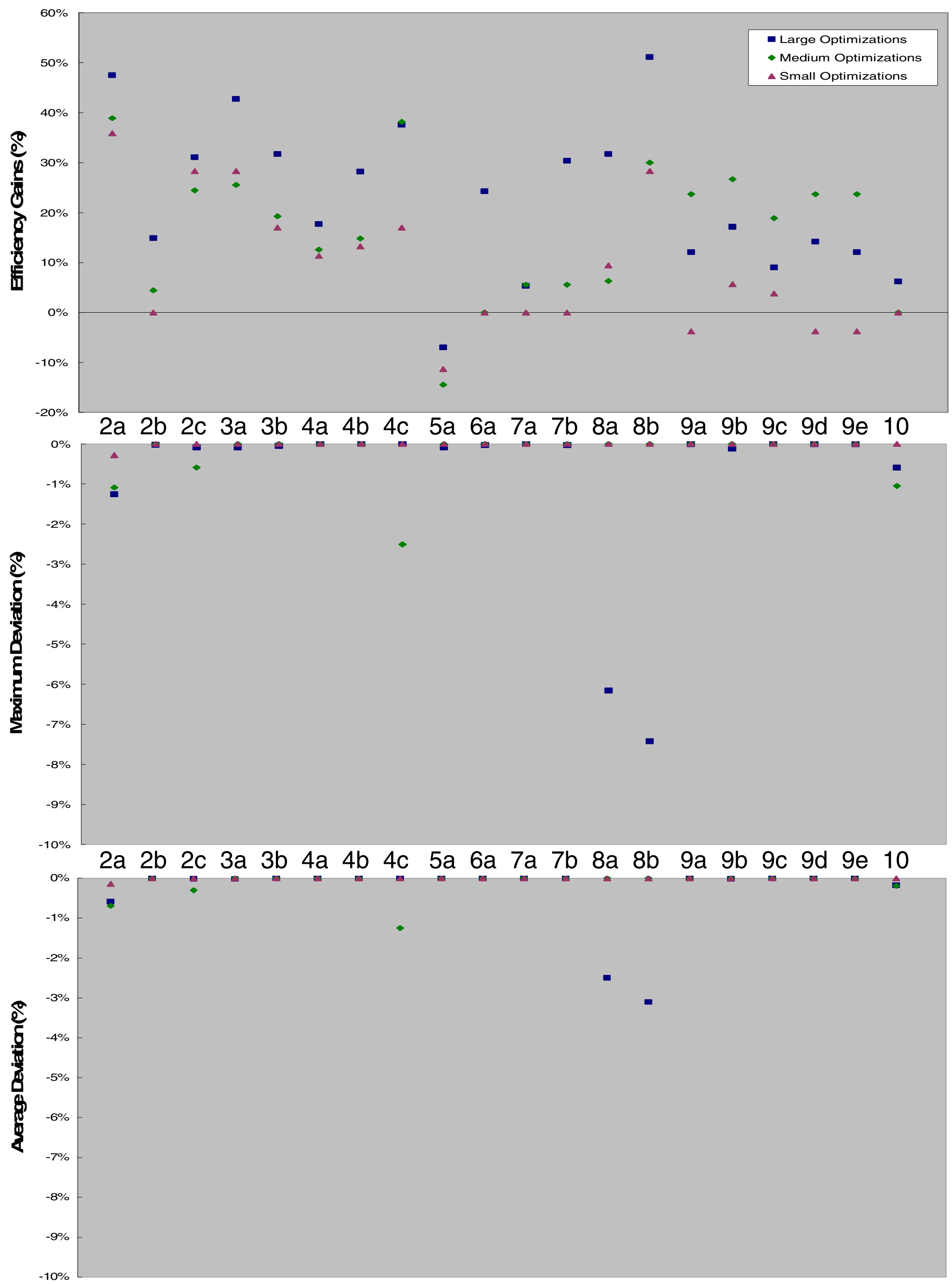

Figure C-5: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, Boulder

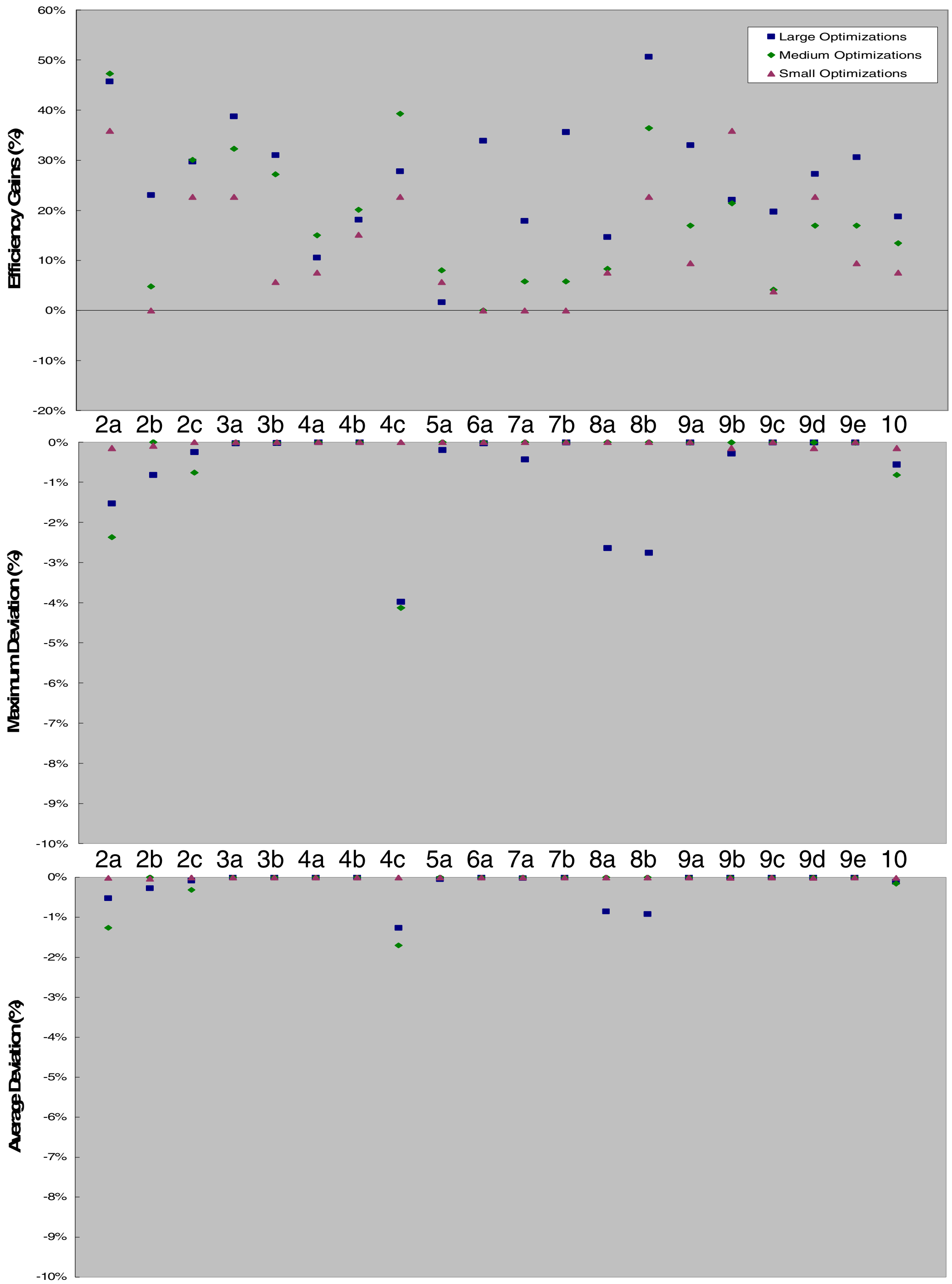

Figure C-6: Efficiency Gains and Avg/Max Deviations, All Efficiency Strategies, Chicago

Appendix D – Results for Packages

Table D-1: Efficiency Results for All Locations and Sizes

	Number of Simulations							Reduction in Simulations (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	2047	1680	2440	2331	2305	1994	**2133**	--	--	--	--	--	--	**--**
A	1663	1410	2085	1994	1885	1778	**1803**	19	16	15	14	18	11	**15**
B	1364	1311	1906	1711	1448	1153	**1482**	33	22	22	27	37	42	**31**
C	1149	1056	1511	1455	1420	1100	**1282**	44	37	38	38	38	45	**40**
D	869	810	1040	1203	933	826	**947**	58	52	57	48	60	59	**56**
E	653	692	911	782	809	644	**749**	68	59	63	66	65	68	**65**
F	701	583	766	613	735	637	**673**	66	65	69	74	68	68	**68**
G	585	510	683	506	616	527	**571**	71	70	72	78	73	74	**73**
H	547	469	483	383	464	342	**448**	73	72	80	84	80	83	**79**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	272	241	301	241	270	313	**273**	--	--	--	--	--	--	**--**
A	216	187	268	206	232	257	**228**	21	22	11	15	14	18	**17**
B	216	187	268	206	232	257	**228**	21	22	11	15	14	18	**17**
C	179	173	291	171	181	238	**206**	34	28	3	29	33	24	**25**
D	147	128	201	152	149	173	**158**	46	47	33	37	45	45	**42**
E	138	120	190	134	144	167	**149**	49	50	37	44	47	47	**46**
F	120	102	158	89	126	159	**126**	56	56	48	63	53	49	**54**
G	104	96	142	83	120	142	**115**	62	60	53	66	56	55	**58**
H	91	89	111	78	106	106	**97**	67	63	63	68	61	66	**65**
Small Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**
Ref.	60	46	73	60	53	53	**58**	--	--	--	--	--	--	**--**
A	43	44	64	64	45	49	**52**	28	4	12	-7	15	8	**8**
B	43	44	64	64	45	49	**52**	28	4	12	-7	15	8	**8**
C	41	37	64	60	46	44	**49**	32	20	12	0	13	17	**17**
D	33	35	53	56	36	39	**42**	45	24	27	7	32	26	**26**
E	33	35	53	46	36	39	**10**	45	24	27	23	32	26	**26**
F	31	32	35	40	35	36	**35**	48	30	52	33	34	32	**32**
G	27	28	33	35	34	33	**32**	55	39	55	42	36	38	**38**
H	26	28	32	34	33	33	**31**	57	39	56	43	38	38	**38**

Table D-2: Robustness Results for All Locations and Sizes

	Average Deviation (%)							Maximum Deviation (%)						
Large Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
A	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
B	0.00	0.00	0.00	0.00	0.01	0.00	**0.00**	0.02	0.00	0.00	0.01	0.03	0.03	**0.03**
C	0.00	0.00	0.00	0.06	0.01	0.00	**0.01**	0.02	0.06	0.00	0.25	0.03	0.00	**0.25**
D	0.01	0.00	0.01	0.11	0.02	0.03	**0.03**	0.12	0.06	0.08	0.25	0.23	0.25	**0.26**
E	0.01	0.01	0.01	0.22	0.02	0.03	**0.05**	0.12	0.06	0.08	0.84	0.23	0.26	**0.84**
F	0.01	0.01	0.01	0.21	0.05	0.00	**0.05**	0.15	0.06	0.08	0.78	0.23	0.02	**0.78**
G	0.20	0.01	0.00	0.29	0.12	0.00	**0.10**	0.43	0.09	0.07	1.22	0.63	0.02	**1.22**
H	0.39	0.76	1.62	0.67	1.51	0.26	**0.87**	0.88	2.21	3.79	3.92	3.33	0.63	**3.92**
Medium Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
A	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
B	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
C	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
D	0.00	0.00	0.12	0.00	0.00	0.00	**0.02**	0.00	0.00	0.77	0.00	0.00	0.00	**0.77**
E	0.00	0.00	0.12	0.00	0.00	0.00	**0.02**	0.00	0.00	0.77	0.00	0.00	0.00	**0.77**
F	0.00	0.00	0.10	0.01	0.04	0.01	**0.03**	0.00	0.00	0.90	0.11	0.52	0.01	**0.90**
G	0.34	0.03	0.10	0.02	0.06	0.02	**0.10**	0.52	0.44	0.90	0.11	0.94	0.20	**0.94**
H	0.87	0.07	0.82	0.05	1.25	0.54	**0.60**	1.70	1.19	2.07	0.12	2.88	0.95	**2.88**
Small Optimizations														
	Pho	Hou	Atl	S.F.	Bou	Chi	**Avg**	Pho	Hou	Atl	S.F.	Bou	Chi	**Max**
A	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
B	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
C	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**
D	0.06	0.00	0.00	0.00	0.00	0.00	**0.01**	0.75	0.00	0.06	0.00	0.00	0.00	**0.75**
E	0.06	0.00	0.00	0.04	0.00	0.00	**0.02**	0.75	0.00	0.06	0.24	0.00	0.00	**0.75**
F	0.00	0.01	0.00	0.04	0.00	0.00	**0.01**	0.00	0.04	0.06	0.24	0.00	0.00	**0.24**
G	0.05	0.02	0.01	0.04	0.00	0.02	**0.02**	0.36	0.09	0.07	0.24	0.00	0.20	**0.36**
H	3.70	0.89	0.31	0.05	0.08	0.02	**0.84**	6.21	1.28	1.72	0.24	0.47	0.24	**6.21**

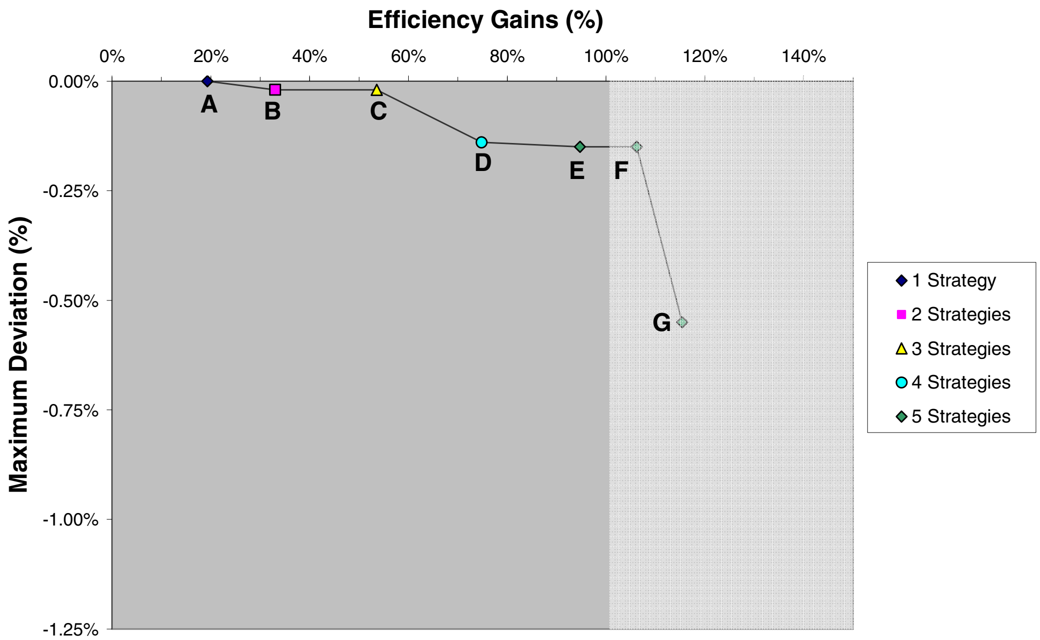

Figure D-1: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, Phoenix

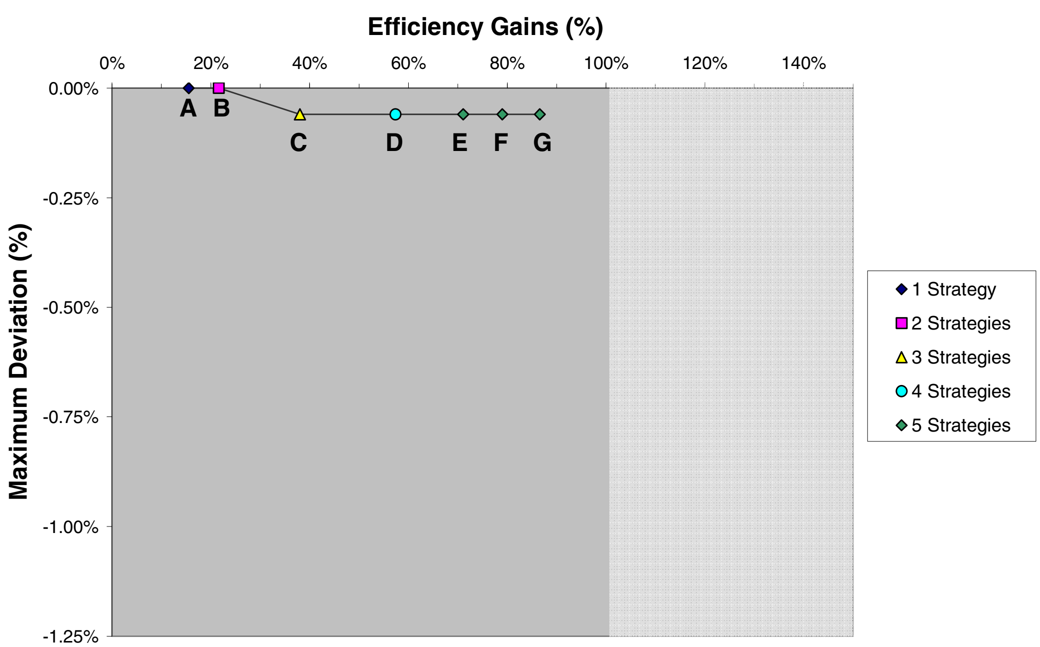

Figure D-2: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, Houston

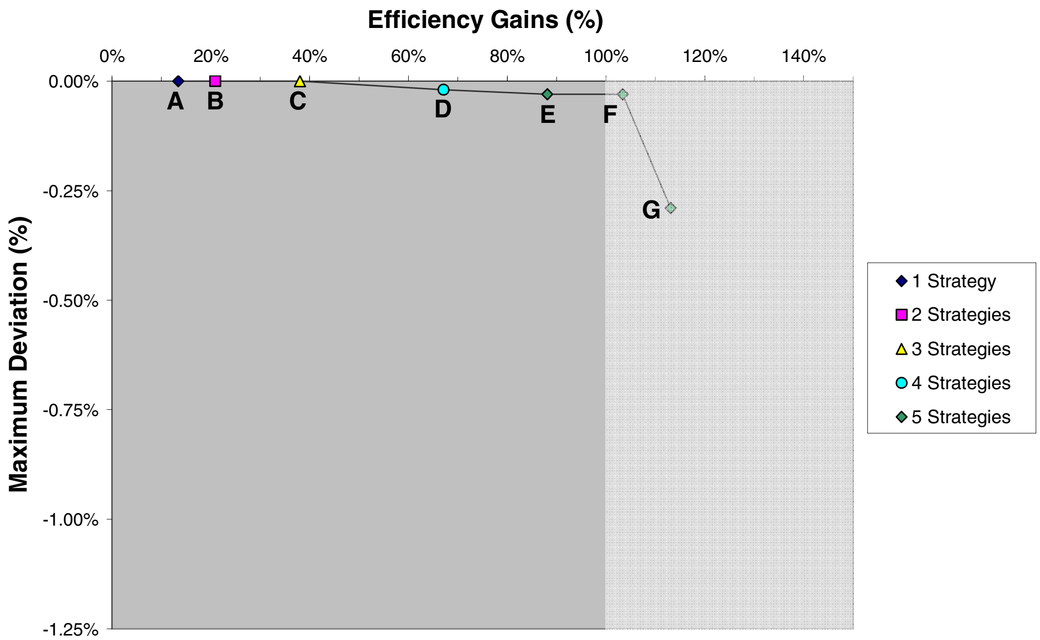

Figure D-3: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, Atlanta

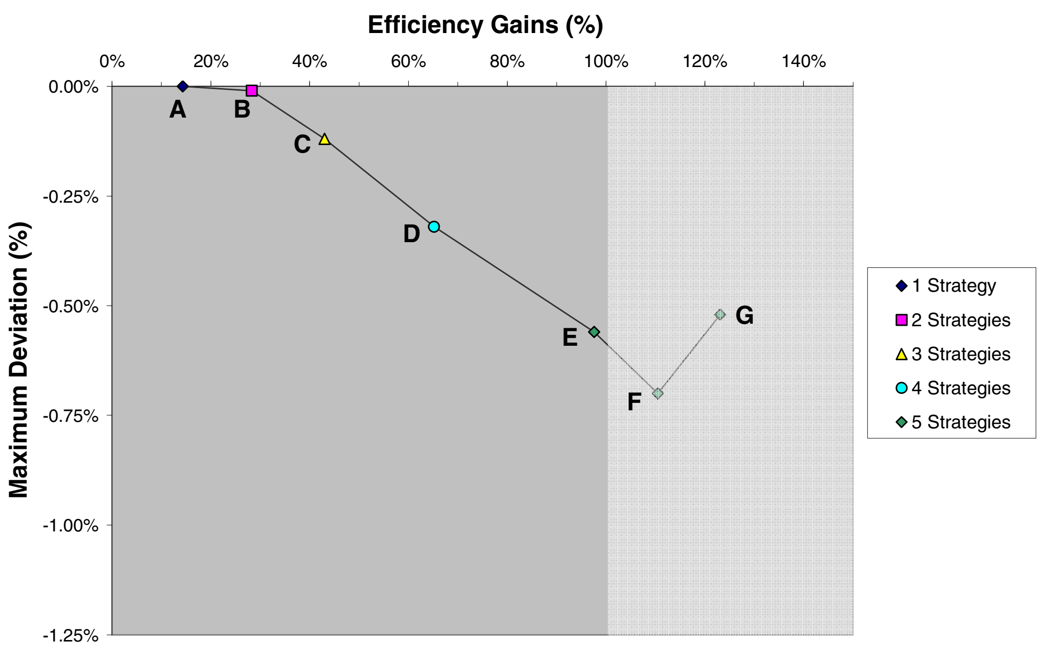

Figure D-4: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, San Fran

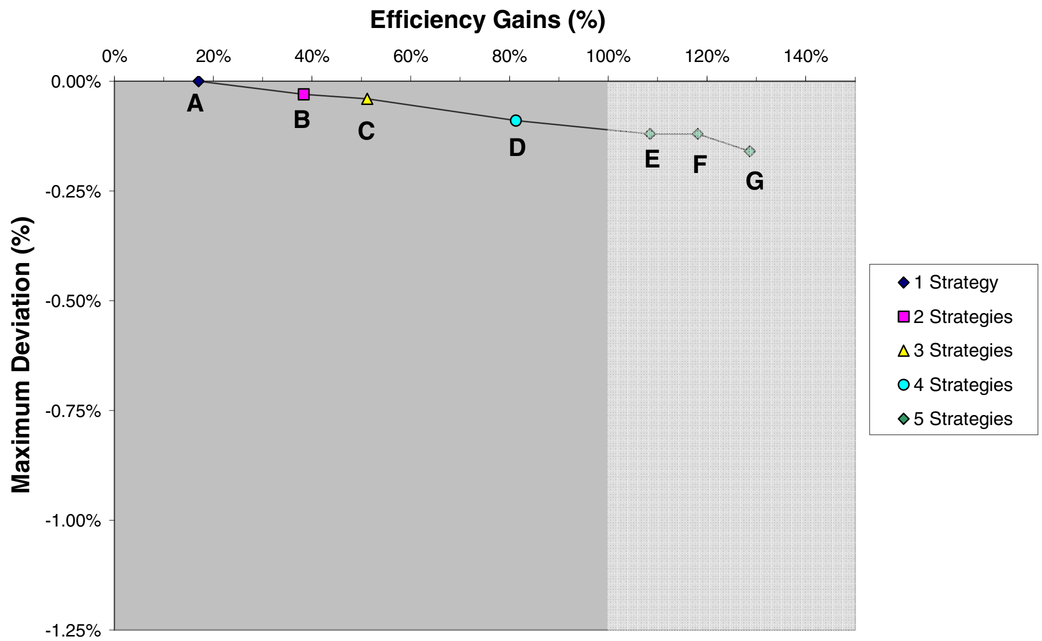

Figure D-5: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, Boulder

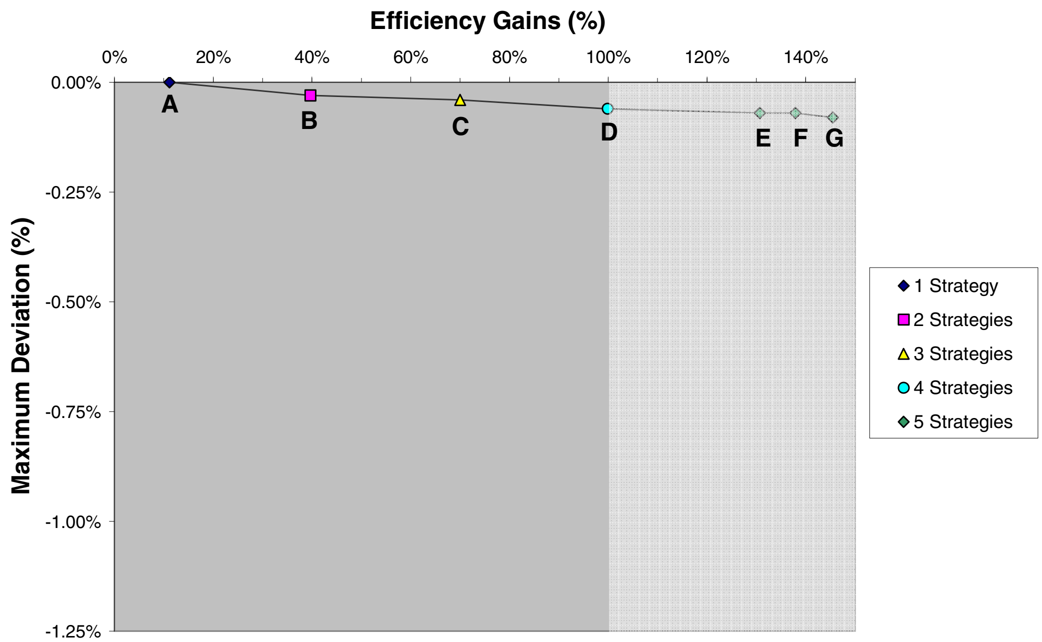

Figure D-6: Packages A-G Based on Predicted Efficiency Gains and Maximum Deviations, Chicago

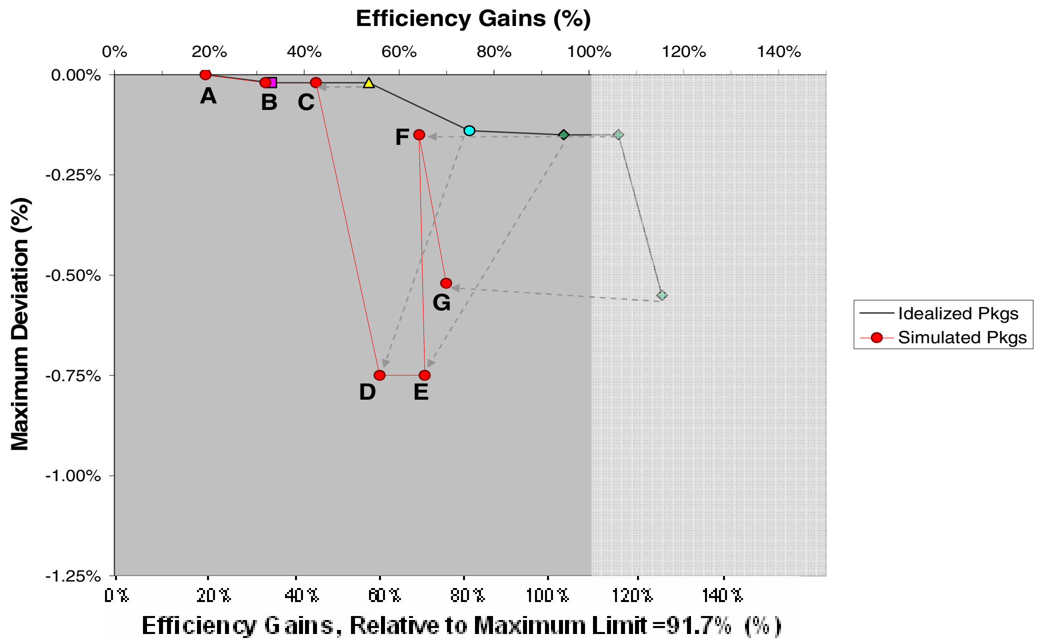

Figure D-7: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, Phoenix

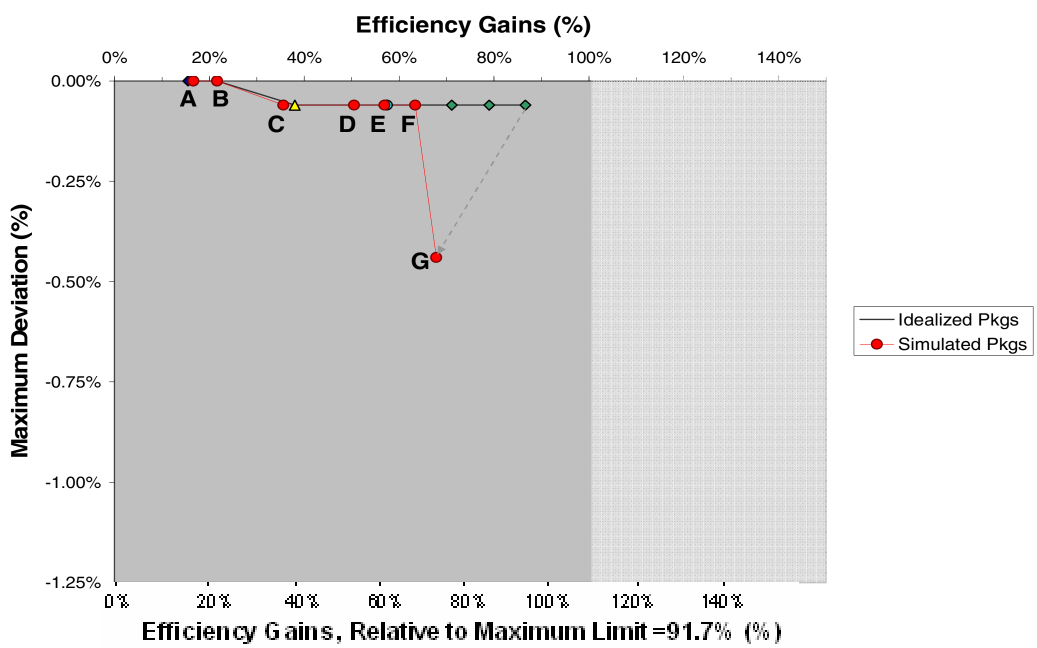

Figure D-8: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, Houston

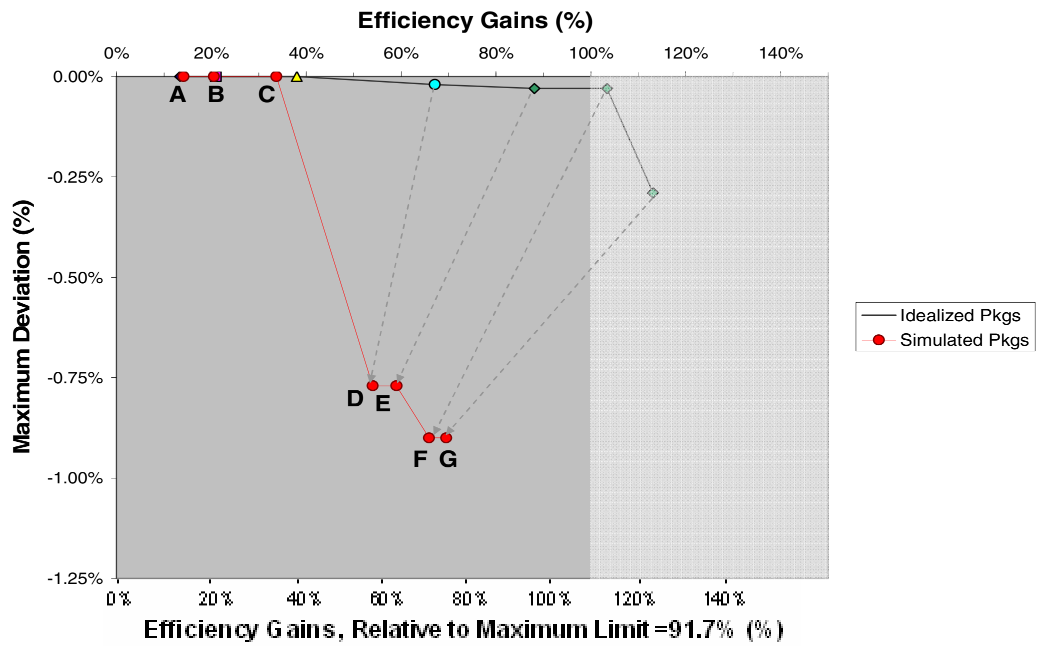

Figure D-9: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, Atlanta

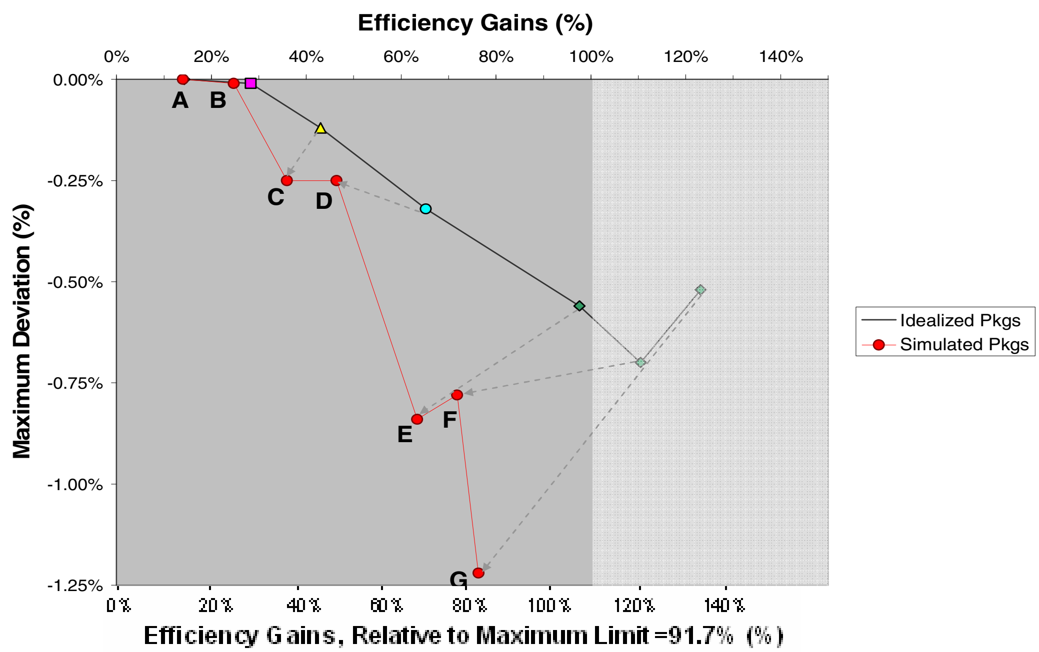

Figure D-10: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, San Fran

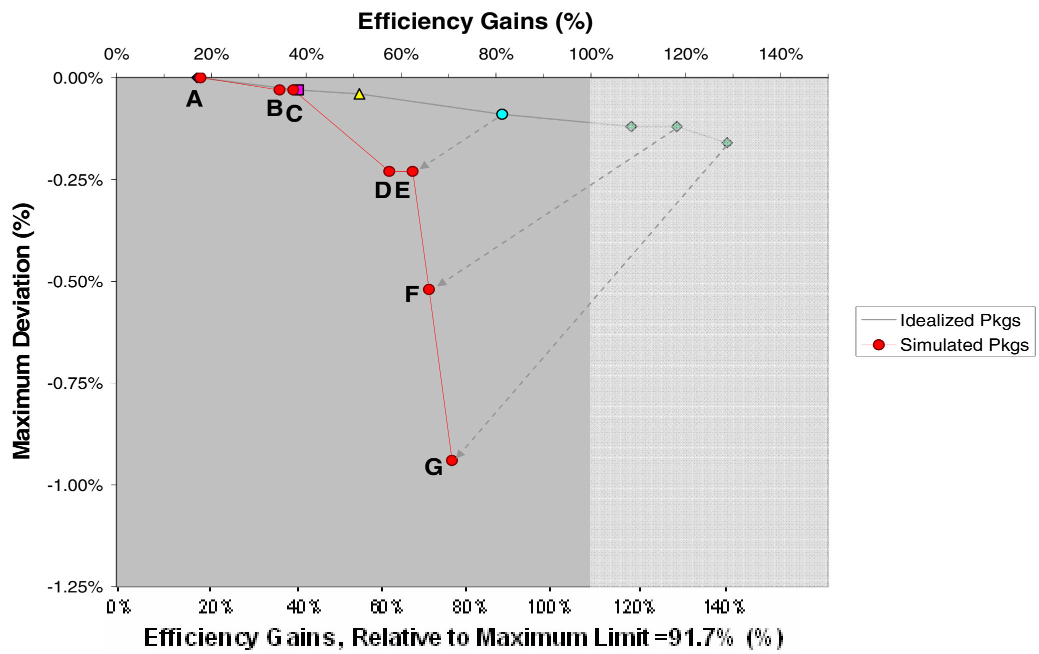

Figure D-11: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, Boulder

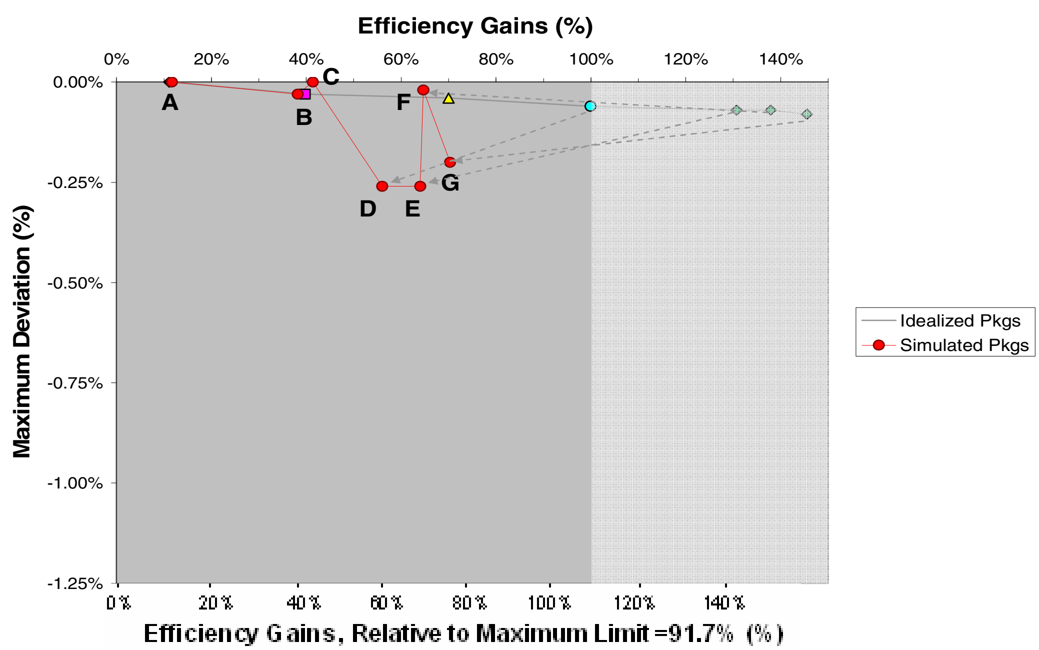

Figure D-12: Simulated/Predicted Pairs for Packages A-G; 33/33/33 Use Profile, Chicago

Table D-3: Simulated Efficiency Gains and Maximum Deviations for all Packages, Phoenix

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	28.3	20.6	18.8	19.2	20.9	0.00
B	28.3	20.6	33.4	31.8	34.7	0.02
C	31.7	34.2	43.9	42.5	46.3	0.02
D	45.0	46.0	57.5	55.9	61.0	0.75
E	45.0	49.3	68.1	65.4	71.3	0.75
F	48.3	55.9	65.8	64.2	70.0	0.15
G	55.0	61.8	71.4	69.9	76.2	0.52
H	56.7	66.5	73.3	72.1	78.6	6.21

Table D-4: Simulated Efficiency Gains and Maximum Deviations for all Packages, Houston

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	4.3	22.4	16.1	16.6	18.1	0.00
B	4.3	22.4	22.0	21.6	23.6	0.00
C	19.6	28.2	37.1	35.6	38.8	0.06
D	23.9	46.9	51.8	50.5	55.1	0.06
E	23.9	50.2	58.8	56.9	62.1	0.06
F	30.4	56.4	65.3	63.4	69.1	0.06
G	39.1	60.2	69.6	67.8	73.9	0.44
H	39.1	63.1	72.1	70.2	76.6	2.21

Table D-5: Simulated Efficiency Gains and Maximum Deviations for all Packages, Atlanta

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	12.3	11.0	14.5	14.1	15.4	0.00
B	12.3	11.0	21.9	20.5	22.4	0.00
C	12.3	3.3	38.1	33.7	36.8	0.00
D	27.4	33.2	57.4	54.0	58.9	0.77
E	27.4	36.9	62.7	27.4	29.9	0.77
F	52.1	47.5	68.6	65.9	71.9	0.90
G	54.8	52.8	72.0	69.5	75.8	0.90
H	56.2	63.1	80.2	77.8	84.8	3.79

Table D-6: Simulated Efficiency Gains and Maximum Deviations for all Packages, San Fran

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	-6.7	14.5	14.5	14.0	15.3	0.00
B	-6.7	14.5	26.6	24.7	26.9	0.01
C	0.0	29.0	37.6	35.9	39.1	0.25
D	6.7	36.9	48.4	46.4	50.6	0.25
E	23.3	44.4	66.5	63.4	69.1	0.84
F	33.3	63.1	73.7	71.8	78.3	0.78
G	41.7	65.6	78.3	76.3	83.2	1.22
H	43.3	67.6	83.6	81.2	88.5	3.92

Table D-7: Simulated Efficiency Gains and Maximum Deviations for all Packages, Boulder

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	15.1	14.1	18.2	17.7	19.3	0.00
B	15.1	14.1	37.2	34.4	37.5	0.03
C	13.2	33.0	38.4	37.3	40.7	0.03
D	32.1	44.8	59.5	57.5	62.7	0.23
E	32.1	46.7	64.9	62.4	68.0	0.23
F	34.0	53.3	68.1	65.9	71.9	0.52
G	35.8	55.6	73.3	70.7	77.1	0.94
H	37.7	60.7	79.9	77.1	84.1	3.33

Table D-8: Simulated Efficiency Gains and Maximum Deviations for all Packages, Chicago

Pkg	Efficiency Gains (%)				Efficiency Gains, Relative to Max Limit=91.7% (%)	Max Deviation (%)
	Small Only	Medium Only	Large Only	33/33/33 Use Profile	33/33/33 Use Profile	
A	7.5	17.9	10.8	11.7	12.8	0.00
B	7.5	17.9	42.2	38.2	41.7	0.03
C	17.0	24.0	44.8	41.4	45.1	0.00
D	26.4	44.7	58.6	56.0	61.1	0.26
E	26.4	46.6	67.7	64.0	69.8	0.26
F	32.1	49.2	68.1	64.7	70.6	0.02
G	37.7	54.6	73.6	70.3	76.7	0.20
H	37.7	66.1	82.8	79.6	86.8	0.95

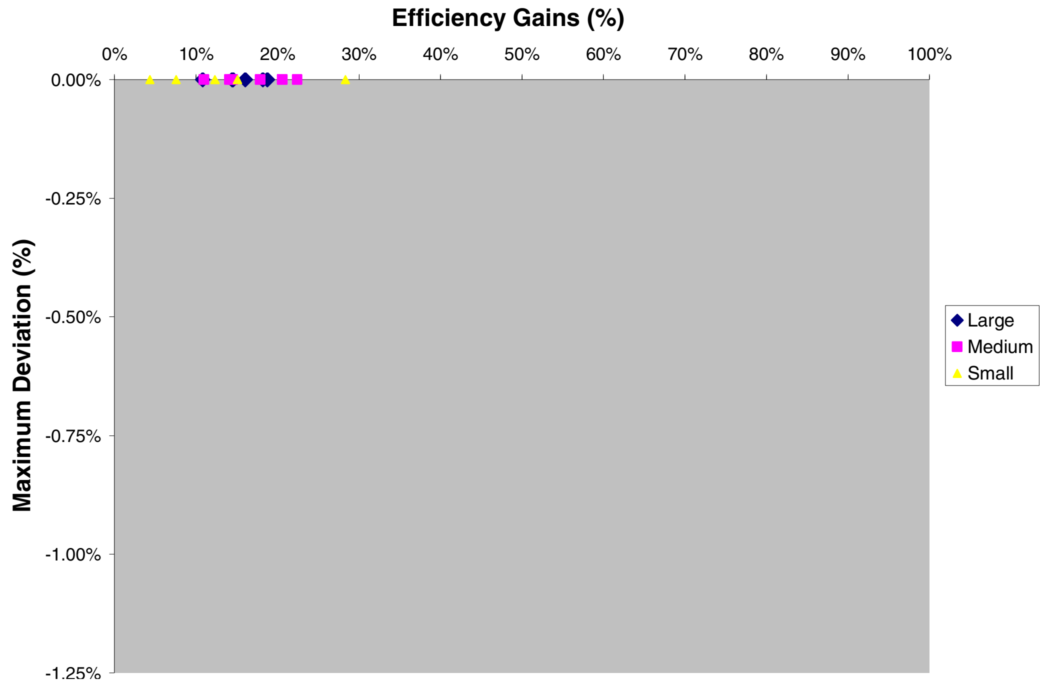

Figure D-13: Simulated Results for Package A, All Climates and Sizes

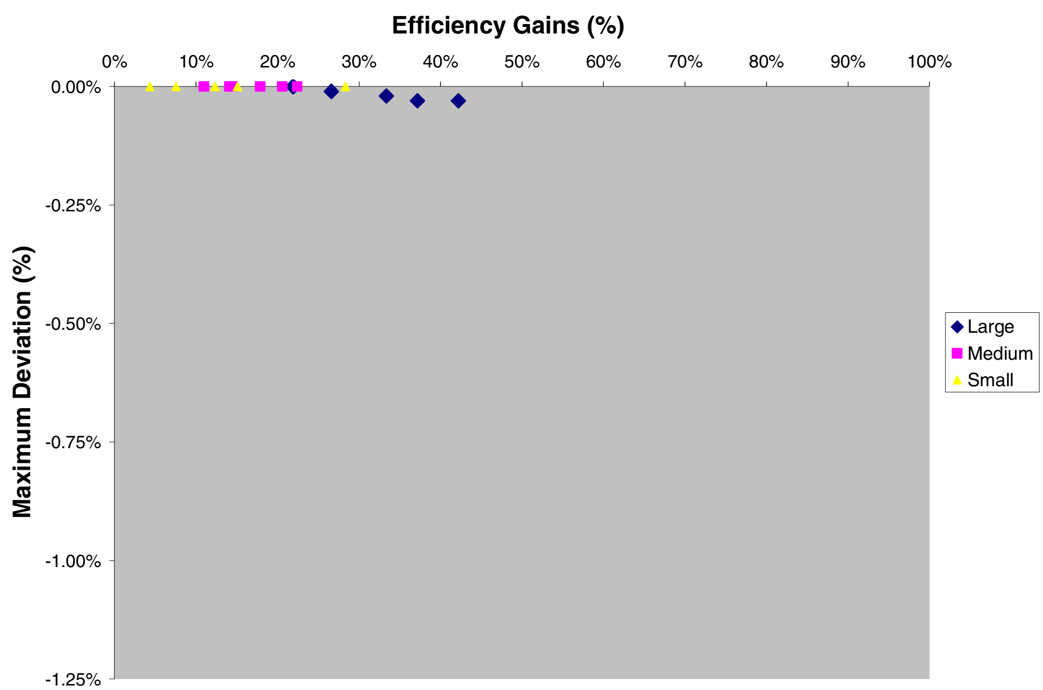

Figure D-14: Simulated Results for Package B, All Climates and Sizes

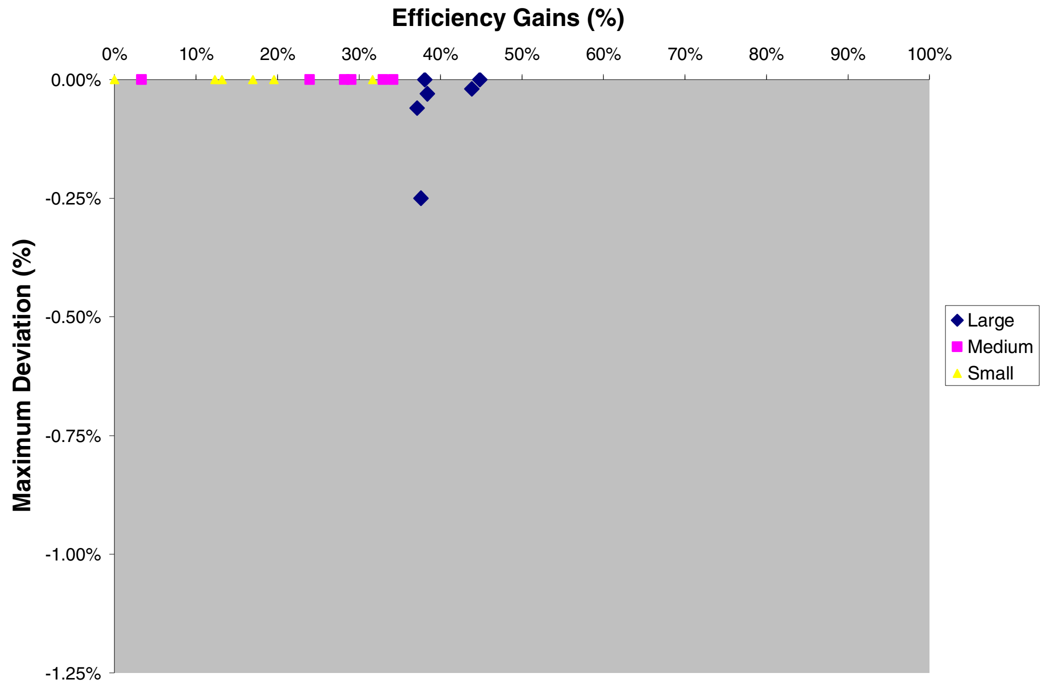

Figure D-15: Simulated Results for Package C, All Climates and Sizes

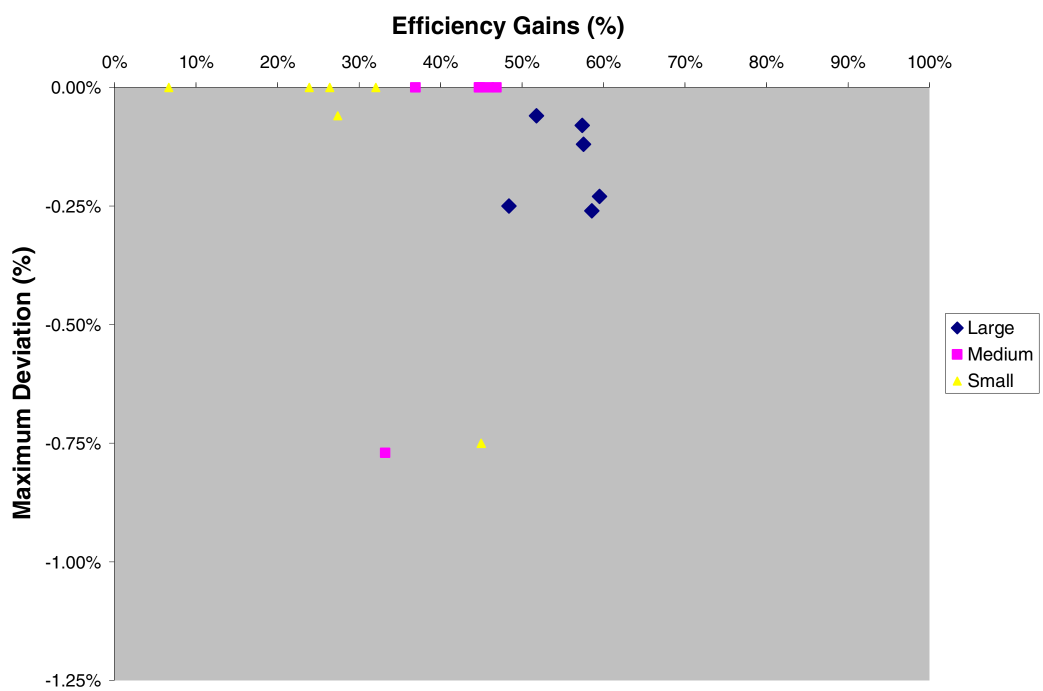

Figure D-16: Simulated Results for Package D, All Climates and Sizes

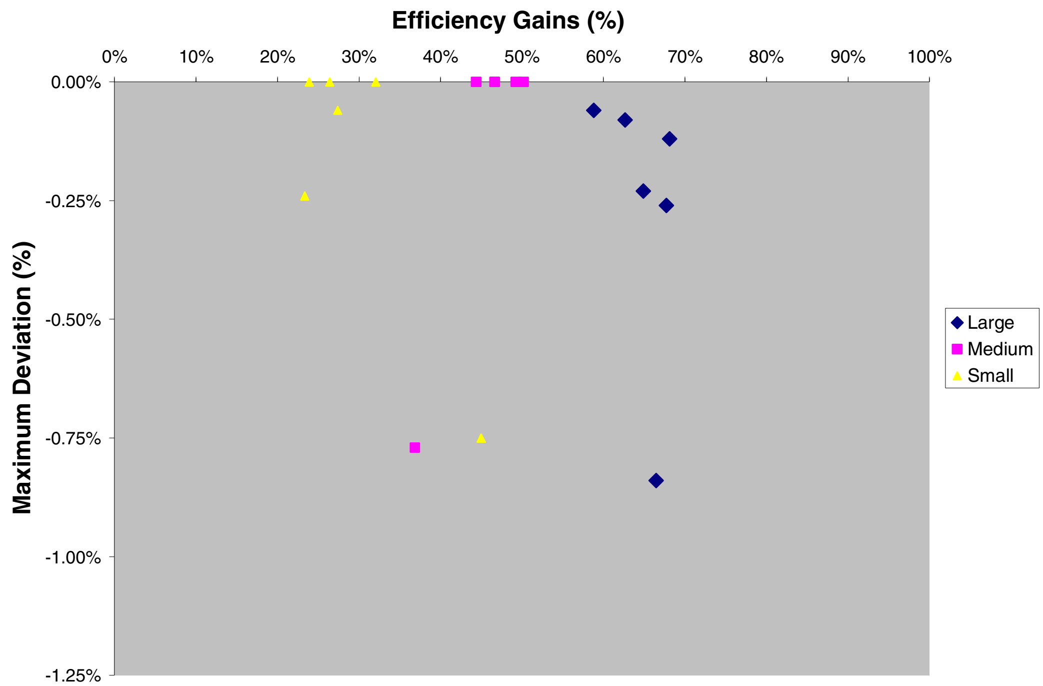

Figure D-17: Simulated Results for Package E, All Climates and Sizes

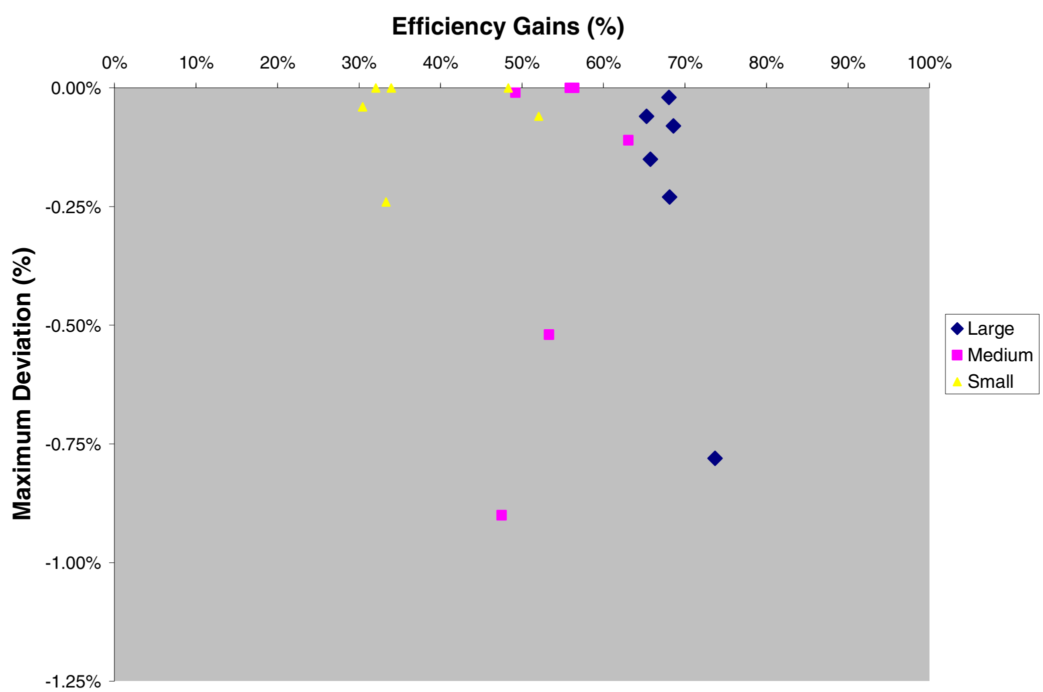

Figure D-18: Simulated Results for Package F, All Climates and Sizes

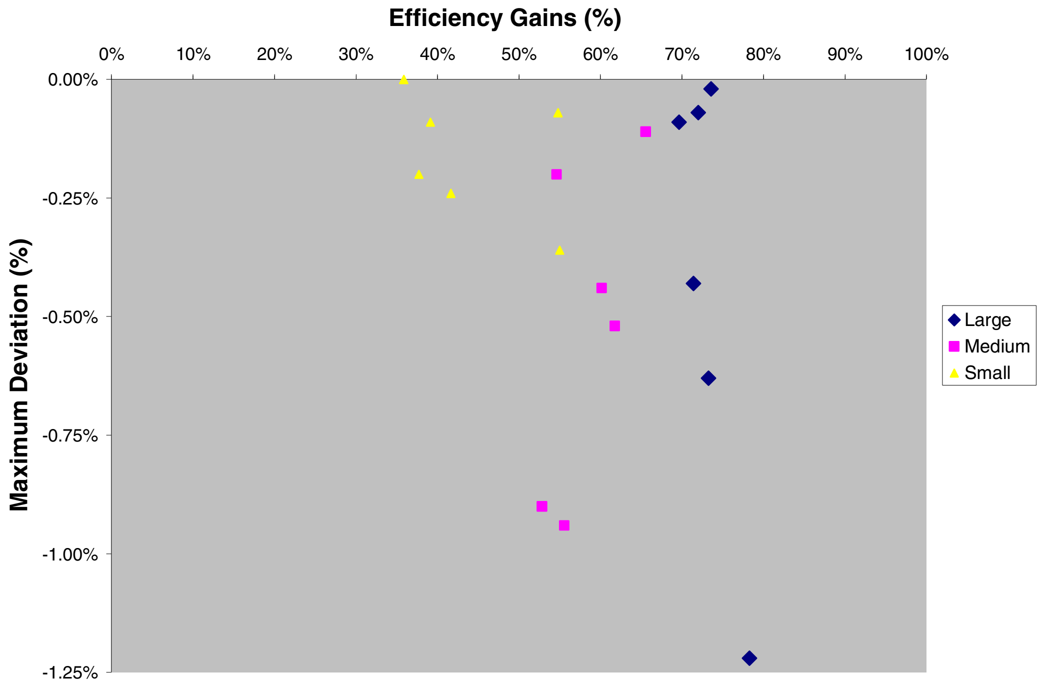

Figure D-19: Simulated Results for Package G, All Climates and Sizes

Appendix E – Well-Ordered and UA Categories

Table E-1: Listing of UA Categories

Categories
Walls
Ceiling
Thermal Mass
Infiltration

Table E-2: Listing of Well-Ordered Categories

Categories	
Walls	Plug-in Lighting
Ceiling	Air Conditioner
Thermal Mass	Furnace
Infiltration	Heat Pump
Refrigerator	Water Heater
Dishwasher	Ducts
Clothes Washer	Solar DHW
Hardwired Lighting	