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AN ENHANCED SEQUENTIAL SEARCH METHODOLOGY FOR IDENTIFYING COST-OPTIMAL BUILDING PATHWAYS

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ABSTRACT

The BEopt™ software is a building energy optimization tool that generates a cost-optimal path of building designs from a reference building up to zero-net energy. It employs a sequential search methodology to account for complex energy interactions between building efficiency measures.

Enhancement strategies to this search methodology are developed to increase accuracy (ability to identify the true cost-optimal curve) and speed (number of required energy simulations). A test suite of optimizations is used to gauge the effectiveness of each strategy. Combinations of strategies are assembled into packages, ranging from conservative to aggressive, so up to 71% fewer simulations are required.

INTRODUCTION

Building Optimization

Building energy optimization entails adjusting building components until a design is identified that achieves minimum cost or energy use. Such optimization is inherently multivariate; the parameter search space includes a range of options for envelope constructions, HVAC, appliances, lighting, geometry and form, renewable generation, and so on.

In the practice of designing real buildings, discrete solutions describe building packages that can be physically built. Genetic algorithms (GAs) are most commonly used for building energy optimizations that use hourly simulations (Wetter 2004b). GAs have been used in building energy applications by Wright and Loosemore (2001) and Caldas and Norford (2002). Other discrete optimization algorithms include Simulated Annealing and TABU.

Many optimization methodologies strive to identify the global optimum, the single building design that minimizes costs. Others seek to develop the Pareto Frontier – the set of cost-optimal solutions over a range of energy savings.

Building Energy Optimization Tools

Davis Energy Group developed a spreadsheet-based methodology for its ACT^2 project (1993). The process performs evaluations of energy efficiency measures via simulations in a sequential analysis method that explicitly accounts for energy interactions.

GenOpt (Wetter 2004a), developed at Lawrence Berkeley National Laboratory, is a generic optimization program that hooks into external simulation engines to minimize a cost function. It includes continuous and discrete methodologies.

EnergyGauge Pro (2004), developed by the Florida Solar Energy Center, contains successive incremental optimization. The optimization process provides a recommended energy efficiency upgrade package to the user based on specified energy and cost goals.

The BEopt Software

The BEopt software (Christensen et al. 2005), developed by the National Renewable Energy Laboratory (NREL), is a computer program designed to identify cost-optimal building designs at a variety of energy savings levels, typically spanning from a reference building to zero net energy (ZNE).

The BEopt library provides predefined options in various categories (wall type, ceiling type, window glass type, HVAC type, etc.). These options can be selected for consideration in the optimization. The DOE-2 (York and Cappiello 1981) and TRNSYS (Klein et al. 1996) simulation engines are called to automate the process of finding optimal building designs.

A conceptual plot of BEopt's cost/energy graph is illustrated in Figure 1. Costs on the y-axis are composed of utility bills and incremental mortgage costs relative to a reference building. At the starting point, point A, utility bills make up the entire building's energy-related costs. 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).

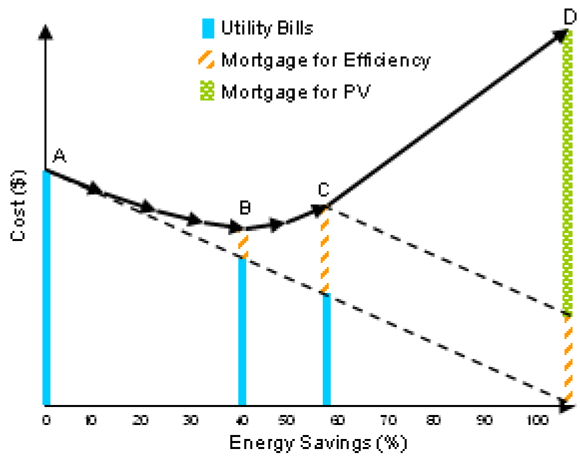

Figure 1 BEopt's Pathway to ZNE

Additional efficiency measures are introduced until the marginal cost of saved energy equals the marginal cost of producing photovoltaic (PV) energy (point C). At this point, PV capacity is added until all source energy use is offset (point D).

Basic Sequential Search

To generate the path illustrated in Figure 1, the BEopt software currently employs a modified version of the basic sequential search optimization strategy (Christensen et al. 2004) that incorporates the accuracy strategies presented later in this paper. The search strategy provides: 1) intermediate optimal points (minimum cost designs at various levels of energy savings); 2) discrete, realistic building packages, and 3) near-optimal alternative designs.

The basic sequential search process entails evaluating efficiency measures across categories to determine the most cost-effective option at each sequential point along the path to ZNE.

All options are simulated one by one in the presence of an initial building design. These simulations comprise an iteration, or stage, of the optimization process. As illustrated in Figure 2, the most cost-effective (steepest slope) option, based on simulation results and energy-related costs, is chosen as the optimal point for the iteration. The chosen option is then removed from future evaluation by the search. Remaining efficiency measures are simulated in the presence of this new optimal point and the iterative process repeats.

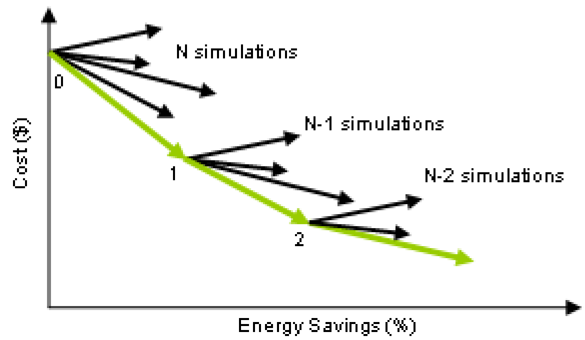

Figure 2 Basic Sequential Search Process

Upon the conclusion of each iteration, the marginal cost of the most cost-effective efficiency measure is compared to the cost of producing 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.

ACCURACY STRATEGIES

By virtue of re-simulating efficiency measures upon each iteration, the sequential search process accounts for energy interactions between parameters. However, additional shortcomings of the search remain and are addressed below.

Large-Step Special Case

The large-step (LS) special case is a deficiency in the basic sequential search methodology that arises from searching for the next optimal point (or, the next steepest slope increment) within the set of buildings simulated during the current iteration only. In some circumstances, the next steepest slope building could actually come from a previous iteration (Figure 3).

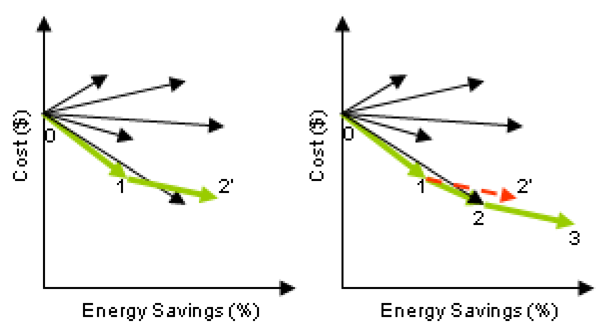

Figure 3 Large-Step Special Case

Therefore, retaining information about every simulated point during the optimization process helps ensure that the true cost-minimum path is identified.

Invest/Divest Special Case

The basic sequential search methodology typically works by making incremental improvements to all components of the building in parallel. However, at the point where the building has achieved large savings in multiple sectors of energy efficiency (e.g. building envelope and space conditioning equipment), it may be more cost-effective to invest aggressively in one sector and subsequently divest in the other. This is because the latter sector performs less effectively in the presence of the other sector's large investment.

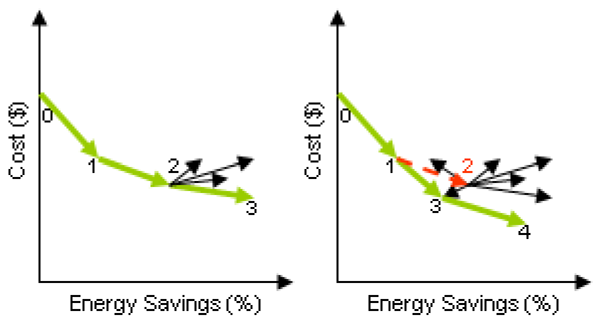

Figure 4 Invest/Divest Special Case

Figure 4 illustrates the solution to the invest/divest (I/D) special case – "looking backward." That is, the search continues to simulate efficiency measures even after they have been superseded by more efficient options during the optimization process.

Positive Interaction Special Case

The two previous special cases involve negative interactions, where the energy savings of a set of efficiency measures is less than the sum of savings for each individual efficiency measure. This last deficiency in the basic sequential search methodology instead involves positive interactions (Figure 5).

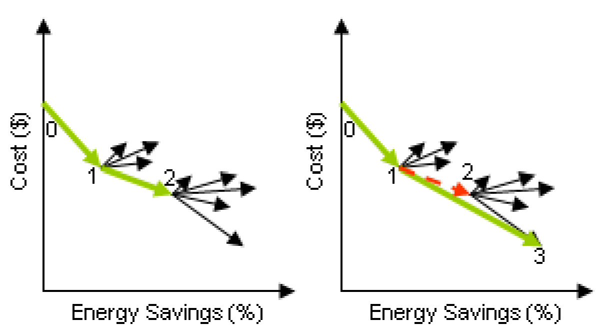

Figure 5 Positive Interaction Special Case

A passive solar building depicts such a scenario. The cost/energy performance of either extra south-facing window area in a "light" building (little thermal mass) or additional thermal mass in a building with nominal south-facing window area may be poor. But the combination of extra south-facing window area and additional thermal mass can perform better than the mathematical sum of individual components.

Because the basic sequential search evaluates efficiency measures one at a time, the search would only evaluate the above passive solar combination if one of the individual measures also performed well and was chosen as an optimal point.

Allowing the user to explicitly specify combinations of options to be evaluated during each iteration of the search would prevent these positive interactions from being overlooked. Although this approach requires a user to exercise his or her engineering judgment before running an optimization, it provides a flexible framework for evaluating any potential positive interactions without causing too large an increase in simulations.

SPEED STRATEGIES

Two approaches for increasing the speed of the search are 1) reducing the number of simulations per iteration; and 2) reducing the number of iterations. Table 1 summarizes various strategies that will be described in subsequent sections. All speed strategies inherently increase the risk of missing optimums; the balance between speed and robustness is addressed in the Results section.

Table 1 List of Speed 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	
4. Skip predicted outliers	
5. Mathematically filter points	
6. Skip fine options	
7. Skip extraneous options	
8. Simulate best ranked option	

1. Modularized Simulations

Typical modeling practices use a single, integrated building simulation to calculate energy impacts of building loads, hot water use, renewable energy generation, and so on. An alternative modeling approach splits the building simulation into modular components (in our case, three – envelope and equipment, hot water, and PV). This occurs at the expense of neglecting small interactions across the components (changes in internal loads from hot water appliances, etc.) and the inability to model certain integrated components (e.g., building integrated PV). Summing each individual simulation result yields whole building energy use and production.

Assuming that each of the *n* modular simulations runs in one-*nth* the time of the integrated simulation, there would be no impact on total simulation runtime if all *n* simulations were run for each building design. But coupling modularization with the sequential search methodology enables runtime gains. Because the search evaluates building designs in an iteration that are one option different than the current optimal point, only a single modular simulation ever has to be performed; the other simulation results can be reused from the optimal point.

The number of required simulations in an optimization is further reduced because some building designs will not need any simulations. Individual simulation results can be retrieved from various points simulated during previous iterations, and energy use and production for the new building can be constructed solely from previous simulation results. The net effect is that using the modular approach reduces simulation runtime to less than one-*nth* that of an integrated approach.

2. Skip Superseded Options

Superseded options refer to measures that were in a given optimal point's building design at one time during the optimization but have since been replaced by more efficient options. Recall that the I/D special case involves searching these superseded options for possible optimal points that might otherwise be missed. This speed strategy evaluates the impact of inactivating the I/D strategy to various degrees.

For example, variants involve simulating only the last superseded option (rather than all superseded options) in a category (Variant 2b) or applying this strategy only to well-ordered categories (Variant 2c). 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.

3. Skip Less Efficient Options

This strategy involves the idea that options of increasing energy efficiency are of more interest the further the optimization proceeds. It entails skipping options that are less energy-efficient than the option in the current optimal point for well-ordered categories. 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 of this strategy attempt to provide a bridge backward to less efficient options. This can involve simulating the single less efficient option (Variant 3b), simulating a random less efficient option (Variant 3c), or cycling through all less efficient options (one per iteration) (Variant 3d). Additionally, an interesting hybrid variant entails skipping less efficient options except for the last superseded option (Variant 3e).

4. Skip Predicted Outliers

Only points near the cost-minimum boundary of the curve are of primary importance; points found outside this lower band ought to be avoided whenever possible. These outlying building designs have little benefit and represent wasted simulations.

By keeping track of (and continuously updating after each iteration) predictions for all efficiency measure based on known information from actual simulations, a threshold band (Figure 6) is used to determine which building designs to simulate in the next iteration.

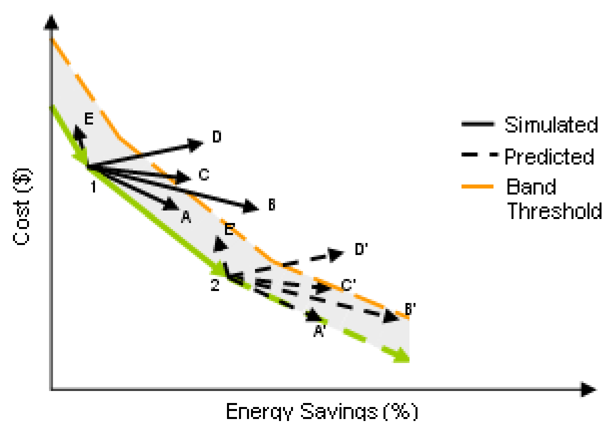

Figure 6 Skip Predicted Outliers Strategy

The band threshold is set based on the specified percentage of the lower cost-optimal curve. For regions where the curve has not yet been generated (to the right of optimal point 2), the best prediction (A') is extrapolated forward.

Variants of this strategy involve altering the band tolerance – e.g. a 5% (Variant 4a), 3% (Variant 4b) or 2% threshold (Variant 4c). Lower band tolerances will achieve higher efficiency gains, but at increased risk of finding suboptimal building designs. Other variants include variable tolerances such that the band tolerance is set more conservatively for the user's target energy savings region (Variant 4d).

5. Mathematically Filter Points

Simulations might be avoided by determining that steeper slopes cannot be attained for certain options with high capital costs compared to options with lower capital costs and known, simulated energy savings.

Suppose that window distribution and ceiling insulation options are to be evaluated in an all-electric building. During an iteration, the window distribution option is simulated and achieves energy savings along the cost of electricity line (Figure 1), because redistributing window area has zero capital cost. The higher ceiling insulation option cannot possibly yield a steeper slope than the window distribution option because of its capital cost. Thus, the simulation can be avoided.

This same logic can be applied to any two options with non-zero capital costs. In these cases, however, predictions about possible energy savings can be used to determine if an option's predicted slope can be steeper than the current iteration's steepest slope.

6. Skip Fine Options

Optimization runtime is intimately tied to the number and range of options within the search space. Plug-in lighting, for example, comprises a tiny percentage of building energy use. Two plug-in lighting options that vary by 10% compact fluorescent lamp increments can result in nearly identical energy use.

To prevent such fineness of options, simulation results are explored at the conclusion of the first iteration. If two options within a single category have essentially equivalent energy savings, the option with lower capital cost is chosen as the better of the two, and the other is skipped from future simulations.

The relationship between options can vary significantly as the optimization proceeds, so only certain categories are eligible. Categories are flagged in advance if differences in energy use between the category's options stay fixed or decrease, regardless of how the building evolves during the optimization.

A variant of this strategy involves reducing simulations across categories for options with essentially equivalent energy savings (Variant 6b). For example, suppose that a wall and ceiling option are essentially equivalent across all their end use results. Because both options are envelope measures (and affect the conductive building load coefficient, UA), the difference in energy savings between the two will be reduced as the optimization proceeds. Therefore the strategy variant could skip the option with higher capital cost until the option with lower capital cost is first chosen.

7. Skip Extraneous Options

Upon completing an iteration of the sequential search, each category is evaluated for extraneous options – those options that fall above the lower boundary of a category's curve (Figure 7).

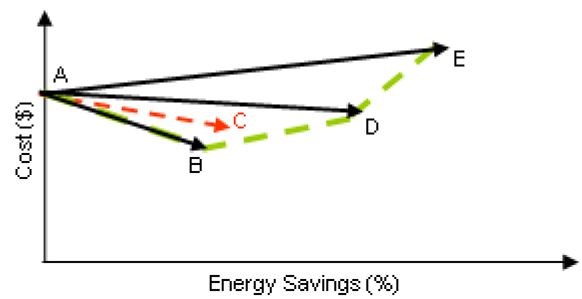

Figure 7 Extraneous Point within a Category

If the relationship between options in a category remains relatively constant throughout the search, option C, the extraneous option, would never be chosen by the search. Extraneous options can arise from discontinuities in a category's cost curve, for example.

One variant applies the strategy only to envelope (UA) categories (Variant 7a) because these categories will tend to cause the results from the figure to compress horizontally, excluding second-order effects. Another variant applies to well-ordered categories (Variant 7b).

8. Simulate Best Ranked Option

A zealous speed strategy entails simulating only the single, next ranked option within a category based on an option ranking developing during the search's first iteration. As demonstrated in Figure 8, the same iterative process used for identifying extraneous points is now used to rank each option within its category.

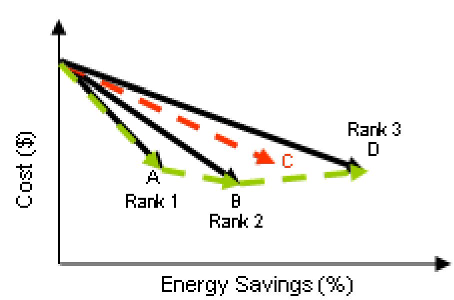

Figure 8 Progressive Ranking Process within a Category for Simulate Best Ranked Option Strategy

Options are ranked by progressive slopes such that option A is ranked first, option B second, and option D last. (Extraneous option C is discarded here, too.)

Variants once again involve applying the strategy either to UA categories, the more conservative subset, where the likelihood of the rank order remaining constant is greater, or to well-ordered categories (Variant 8b). Additional variants could dictate evaluating the two next best ranked options (Variant 8c) or the next and previous best ranked options (Variant 8d).

9. Option Lumping

Option lumping reduces the number of iterations in an optimization by lumping together a series of options into a single optimal point. In the absence of energy interactions, such a strategy would generate the correct lower boundary curve. Because interactions do occur, constraints are used, such as the number of options that can be lumped together – 3, in the case of Figure 9.

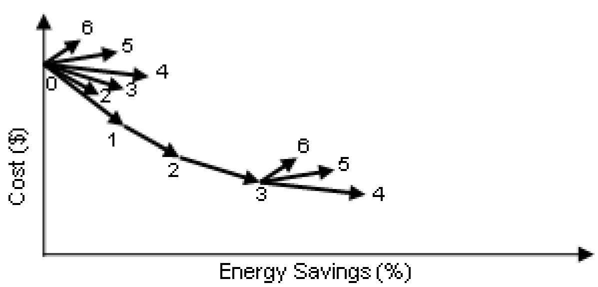

Figure 9 Option Lumping Strategy

Variants can impose additional constraints, such as a maximum amount of cumulative energy savings from the lumped points (e.g., 5%, Variant 9a, or 10% energy savings, Variant 9b). This preserves some caution and can prevent large gaps in the cost-optimal curve.

Another constraint involves 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 the results will deviate from the true lower boundary. Setting this limit to 2 (Variant 9c) or 3 (Variant 9d) can prevent significant divergence.

10. Forward Progression

This strategy forces the sequential search to proceed toward 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 the options in an iteration, but will not choose an option of lesser efficiency for a given optimal point (Figure 10).

With this strategy, the path will diverge to some extent from the true cost-minimum path. But if differences are not significant, we may be better off saving these simulations and proceeding along the path.

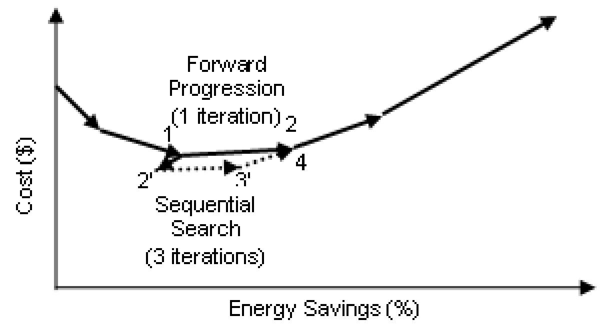

Figure 10 Forward Progression Strategy

RESULTS

Validation

First, there is the question of whether the sequential search (without speed strategies but with the two accuracy strategies, LS and I/D) successfully identifies the true lower boundary of the parameter search space.

Unfortunately, an exhaustive parametric of the search space is prohibitive even with modern processing power. However, about 750,000 simulations can be performed in 5 days worth of runtime across 50 machines using distributed computing capabilities. The results of such an extensive parametric, for a typical residential building in Memphis, are shown as a dense cloud of gray points in Figure 11.

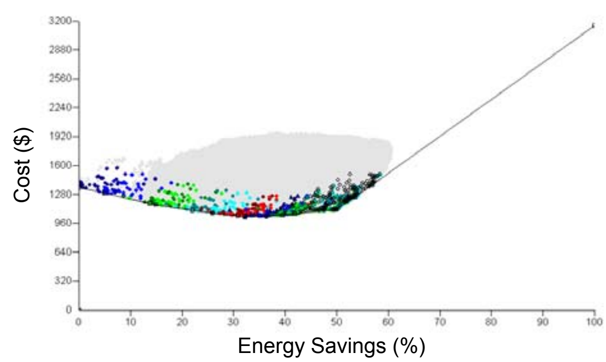

Figure 11 Validation of an Optimization, Superimposed on an Extensive Parametric

An optimization that includes the LS and I/D strategies is then overlaid on top of the parametric using colored points. The optimization contains roughly 2,000 building simulations, fewer than 1% of the number performed during the parametric.

From visual inspection, the results provide a high level of confidence that the techniques identify optimal points within 1%, in terms of total annual cost, of the true lower boundary of the universe of building designs.

Test Suite

To determine the effectiveness (impact on speed and accuracy) of each strategy, a test suite is developed. The test suite is composed of 18 small, medium, and large optimizations (size of the parameter search space) across 6 climates: Phoenix, Houston, Atlanta, San Francisco, Boulder, and Chicago. The building is a typical 2500-square-foot, 2-story residence, with Building America (Hendron 2005) assumptions for operating conditions.

The parameter search space for each optimization spans a number of categories – orientation, neighbors, plug-in loads, heating/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 domestic hot water, and PV.

Option costs are generally derived from RS Means or manufacturer's data. Electricity and natural gas rates are based on Energy Information Administration state average data from 2005.

Characterization of Results

Speed increases are expressed as the percent of saved simulations relative to the number of simulations in the reference optimization. Accuracy results, expressed as maximum deviation, characterize the maximum variation in lower boundary curves between the strategy and reference optimizations, as a percent of the reference optimization's starting point y-value.

Note: Speed strategies (2a through 10) results are relative to reference optimizations that include the accuracy strategies. Results for accuracy strategies (LS and I/D) are obtained by removing the specified strategy from the reference optimization.

Accuracy and Speed

Figure 12 shows speed and accuracy results for 20 speed strategy variants and 2 accuracy strategies along the x-axis (labeled according to their variant numbers). For each strategy, 3 bars show the size of the optimizations' available search space.

Most strategies yield 10-40% savings in required simulations; strategies that bring greatest savings generally incur the largest penalties on accuracy.

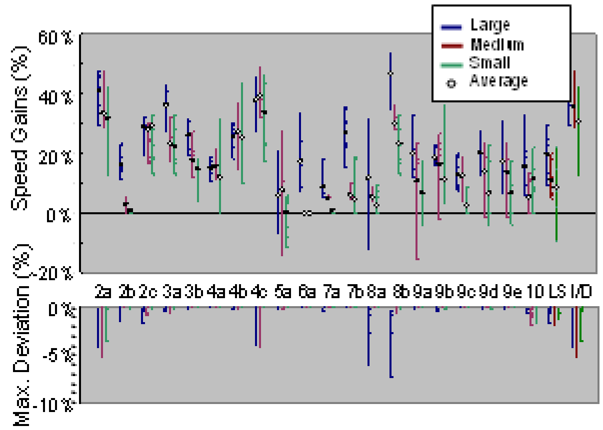

Figure 12 Speed Gains and Max Deviation, All Strategies

Packages

The most effective strategies incorporate speed and accuracy, and are combined into a series of packages ranging from conservative to aggressive (Table 2).

The packages provide a sequence of strategies where each package differs by one strategy, or variant, from its predecessor. Because the net result of combining strategies, due to interactions, is unknown, using a sequence increases the likelihood of producing positive incremental speed gains with each package advance (from A to G) for a given optimization.

Packages A through G are subsequently simulated in the test suite to determine actual speed and accuracy results. Results are also shown in Table 2.

Table 2 Simulated Package Results, from Test Suite

	STRATEGIES	% SPEED GAINS	% MAX DEVIATION
A	4a	15.5	0.00
B	4a, 6a	28.5	0.03
C	4a, 6a, 9a	37.6	0.25
D	4a, 6a, 9a, 3b	53.4	0.77
E	4a, 6a, 9a, 3b, 7e	61.9	0.84
F	4b, 6a, 9a, 3b, 7e	66.2	0.90
G	4b, 6a, 9a, 3a, 7e	70.9	1.22

The packages yield increasing levels of speed gains with modest increases in maximum deviations. Savings in number of simulations range from 16% for the conservative package (0% maximum deviation) to 71% for the aggressive package (1.2% maximum deviation). The theoretical upper limit is less than 100%; that is, an optimization cannot be performed with simulation results unless building simulations are conducted.

Figure 13 illustrates how the results for Package G (shown in red) compare with results for an optimization sans speed strategies (shown in gray). Most of the saved simulations come at higher energy savings where many possible combinations of measures can trade off to achieve these savings. The Package G points are positioned near the lower boundary of the search space and span the entire range of energy savings, as desired.

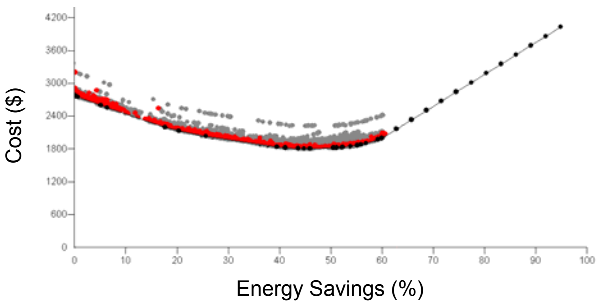

Figure 13 Package G (Red) Superimposed on Its Reference (Gray) for Atlanta, Large Optimization

CONCLUSION

The sequential search methodology is a particularly useful optimization strategy for identifying cost-optimal building designs over a range of energy savings levels. Research in this paper has led to further improvements in the accuracy (ability to generate the true cost-optimal curve) and speed (number of required simulations) of the search.

Three accuracy strategies were developed to address deficiencies in the optimization methodology. Ten speed strategies (and numerous variants) were devised to reduce the number of required simulations.

Combinations of the most effective strategies were developed into successive packages of increasing speed. These combinations range from Package A, the most conservative package that yields 16% speed gains with no effect on accuracy, to Package G, the most aggressive package, which couples all five individual speed strategies and produces 71% speed gains at a maximum deviation of 1.2% for the test suite.

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