A PROCESS FOR, AND RESULTS FROM, WHOLE CAMPUS ENERGY CONSERVATION BY STATISTICAL EXTRAPOLATION OF CALIBRATED ENERGY MODELS

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ABSTRACT

Building performance simulation and energy modeling has traditionally been focused upon the accurate modeling of the physical performance realities of a single, distinct building. Many modern institutions such as hospital complexes, higher education campuses, military bases and other large facilities consist of multiple buildings. Demonstrating the energy saving impacts of campus-wide building repairs and upgrades has proven to be a daunting task for a professional community focused upon the modeling of single buildings.

The immediate objective of this paper is to describe the methods used for developing the University of North Carolina (UNC) Strategic Demand-Side Energy Plan (SDSEP). The SDSEP allows the University of North Carolina at Chapel Hill to identify the energy savings potential for 86 campus buildings from a statistically representative set of 20 buildings. The impact of energy savings within these 20 buildings was modeled using calibrated building energy models in eQuest.

INTRODUCTION

The Strategic Demand Side Energy Plan (SDSEP) project was designed to critically assess the building energy savings potential of UNC and identify which energy conservation measures could be most meaningful to the campus on a space-type basis. In addition to energy savings potential, energy cost avoidance and capital cost estimates were provided to make the dissemination of the SDSEP more effective in stating the opportunities available to UNC.

Early project realities showed that creating calibrated energy models for every building on campus would not have been economically feasible. In order to overcome this limitation, the project team utilized a statistical approach to representing the campus buildings by space usage type. By auditing and analyzing a smaller set of buildings and estimating the energy savings for various options in each stand-along building, savings for the entire campus could then be developed using the statistical methods.

PROJECT AND ANALYSIS SCOPE

Creating Boundaries for the Modeling Effort

Analyzing campus energy use and potential for energy conservation required reasonable limits on the scope of the SDSEP Project. The project included 86 campus buildings with footprints 50,000 GSF or greater that are neither tenant-supported nor associated with the UNC Hospitals. UNC energy monitoring data showed that 85% of the campus energy was historically consumed by this set of 86 buildings.

Originally, sample sets of varying sizes were compiled. These different sample sets were capable of representing the energy use of the 86 building population to various levels of statistical significance. However, budgetary constraints further restricted the level to which detailed investigations of individual buildings could be conducted. Sample design studies suggested a set of 20 buildings could be used to represent the energy consumption of the complete population with a projected relative precision of 22%. Relative precision here is defined by the percent error reflected in the energy consumption savings value. For example, a savings of 10,000 kWh considering the projected relative precision would yield a savings range of 7,800-12,200 kWh. This level of precision was determined sufficient by the project team.

Sample Building Selection

The selection of the 20 buildings was motivated by the assumption that there are more similarities between similar space types than there are between aggregated buildings. For example, the office spaces in a lab building are more similar to other office spaces than they are to the laboratory building as a whole. Therefore, the SDSEP project used space types within buildings as the primary study component, and space type was a critical component of developing the sample set. Further detail on the methodology employed for the sample will be described later in this paper.

The total square footage on UNC at Chapel Hill's campus is comprised of 11 'space types' in accordance with North Carolina State Commission on Higher Education Facilities (HEFC) classifications. For the purposes of the SDSEP these 11 space types were combined into six. HEFC space labels and study space type classifications are shown in Table 1.

Table 1: Space Type Classifications

HEFC LABEL	STUDY CLASS	ABBREVIATION
Classroom	General & Study Facilities	GS
General Use		
Study		
Research Labs	Research Labs	RL
Teaching Labs	Teaching Labs	TL
Offices	Offices	OF
Residential	Residential	RF
Special Use	Special & Support Facilities	SS
Support		
Nonassignable	Other	OTHER
Unclassified		
Health Care	EXCLUDED	EXCLUDED

APPLICATION OF STATISTICAL TOOLS

Reducing a Campus to a Manageable Model

Modeling the 86 most energy-intensive buildings on the UNC campus would be an enormous effort, even with a large group of skilled building energy modelers. The ultimate goal of the SDSEP effort was to project the savings of individual technologies across the entire campus, and the technique of stratified ratio estimation was deemed the best approach to sample design and estimation.

Stratified ratio estimation (SRE) works by taking advantage of already known information available for each building on campus. For example, imagine that the project team could determine the energy savings for each potential technology deployed at UNC. The estimated energy savings could be used as a stratification variable, reducing the coefficient of variation for actual savings within each stratum (in this case, the strata would consist of the 86 buildings in the analysis). The use of stratification techniques also allows for variation in sampling fraction within each stratum to reduce the number of projects modeled while maintaining precision. For buildings with small savings, a smaller sample can be used. Those buildings with larger overall savings will have a larger sample size.

Ratio estimation is a technique for making estimates about a population using auxiliary variables. Estimates for a total population can be made based on ratios of survey samples. Predicting campus-wide energy savings from a small sample of energy models necessitates the use of a realization rate, or the ratio of predicted energy savings to actual, achieved energy savings. If the realization rate were known, true energy saving could be predicted with a high degree of accuracy by multiplying the predicted energy savings by the realization rate. Experienced building energy modelers do not expect their savings estimates to exactly match the savings achieved in real life, so the realization rate is typically smaller or large than 1.0. By estimating the realization rate within each strata, it is possible to develop a more accurate estimation of energy savings that could be achieved with random sampling of the campus buildings.

Regression Modeling

When selecting the distribution of sample buildings and space types, the estimated contribution of each building was included in the variability of the savings estimate. Generally, buildings with higher energy use have a wider range of energy savings potential even if they have the same conditioned area as a building that uses less energy. As described previously, within the SRE framework the project team sampled higher variability sites at a higher rate than lower variability sites to reduce the overall variability of the sample. A stratification variable was therefore necessary to include variable energy use across space types when grouping buildings into strata. First, the energy used by each building's component spaces was estimated. To make these estimates, a least squares regression model of floor areas (energy use as the dependent variable) was applied.

UNC provided two years (2006 and 2007) of aggregate energy use data for each of the 86 buildings, resulting in two figures of total annual energy use for each building. For buildings with two years of utility records, the data was averaged to produce a single estimate of annual energy use for each building. A few buildings were opened in 2006, or had renovation work that impacted that year of data. For these buildings, only the single complete year of data was used.

The floor areas by space type (GS_i, RL_i, TL_i, OF_i, Rf_i, $Other_i$, and SS_i respectively for each building) and gross annual energy uses ($Energy_i$) were fed into an ordinary least squares estimate of the form:

$$Energy_i = \beta_1 GS_i + \beta_2 RL_i + \beta_3 TL_i + \beta_4 OF_i + \beta_5 RF_i + \beta_6 Other_i + \beta_7 SS_i$$

The intercept term was held to zero to reflect the assumption that all the energy use in the buildings could be attributed to one of the seven spaces. Table 2 shows the coefficients and associated statistics for this regression. The overall deviation was 0.873, showing that roughly 87% of the variation in energy use between buildings is a result of the constituent floor areas. Every floor area has a coefficient that is statistically significant and different from zero with a 95% level of confidence. All space types except "Other" are statistically significant with a 99.5% level of confidence.

Table 2: Regression Results

	β	**STD. DEV.**	**T-STAT**	**P-VALUE**
GS	150.0	34.2	4.386	.000
RL	1773.5	78.6	22.570	.000
TL	1111.9	108.3	10.267	.000
OF	445.2	75.8	5.876	.000
RF	181.0	59.6	3.038	.003
OTHER	214.5	100.8	2.128	.035
SS	147.5	48.9	3.019	.003

Determining the Stratification Variable, z_i

The space type variables in the analysis are rewritten as;

$SF_1 = GS,\ SF_2 = RL,\ \ldots,\ SF_2 = SS$

such that, for any building i, the total energy use, E, can be written as;

$$E_i = \sum_{j=1}^{7} \beta_j SF_{j,i}$$

The total floor area for the whole set of 86 buildings, FA, can be written as;

$$FA_i = \sum_{j=1}^{7} SF_{j,i}$$

Ultimately, the savings per area for each space type can be expressed as;

$$\alpha_j = \frac{\sum_{i=1}^{n} Savings_{j,i}}{\sum_{i=1}^{n} SF_{j,i}}$$

for each space type as the estimated savings per square-foot based on the sample of selected buildings. Therefore, the estimated savings Y, of any space, j, in a building, i, can be written;

$$Y_{j,i} = \alpha_j SF_{j,i} + \varepsilon_{j,i}$$

where ε is the error associated with each estimate.

The variance for any space type in a given building, $\sigma_{j,i}$, can be written as;

$$\sigma_{j,i} = sd(\varepsilon_{j,i}) = \sigma_0 (SF_{j,i})^{\gamma_j}$$

where the realization rate is some value, γ_j (typically assumed to be 0.8 for each space type). (Framework Team 2004)

Since variation in savings increases with the amount of energy used annually, energy use estimates were included the expected variance. Assuming all $\gamma_j = \gamma$, the variation of each space in each building would be proportioned to the energy use of that space raised to the power of γ. Therefore,

$$\sigma_{j,i} = k(\beta_j SF_{j,i})^{\gamma}$$

Aggregating to the level of each building (where sampling decisions are made) gives us a an estimate of the total savings of any building in the population;

$$Y_i = \sum_{j=1}^{7} \alpha_j \beta_j SF_{j,i} + \varepsilon_{j,i} \text{ where } \varepsilon_i = \sum_{j=1}^{7} \varepsilon_{j,i}$$

Since the variance of a sum of terms is equal to the square root of the sum of squares of the summed terms' variances, the variance associated with each building's estimate, σ_i, can be written;

$$\sigma_i = sd(\varepsilon_i) = k\sqrt{\sum_{j=1}^{7} (\beta_j SF_{j,i})^{2\gamma}}$$

and with the assumptions of stratified sampling, this becomes;

$$z_i = \sqrt{\sum_{j=1}^{7} (\beta_j SF_{j,i})^{2\gamma}}$$

Stratifying by z_i such that the sum of the z_i in each strata are equal will be the most efficient way to stratify the population and designate the sample.

PHASE I - DESIGNING THE SAMPLE TO MODEL

Stratification

Using z_i for each building as the stratification variable, the population was divided into four strata. The six buildings expected to contribute the most uncertainty were placed in a certainty stratum (100% chance of selection) and the rest of the sample were drawn equally from the sites remaining in the other four strata. In discussions with UNC, it was determined that a target relative precision for the phase II sample design would be 18% with a 90% level of confidence. Assuming an error ratio across the space types of 0.8, the project team determined that a sample of 35 buildings would provide a satisfactory level of relative precision (18%). With no prior studies of this nature on which to base an error ratio, one was intuitively selected. An error ratio 0.5 is much lower than expected in a building stock as widely varied as UNC's, while 1.0 is too conservative given the amount of information in the sample design. As a starting point, an error ratio of 0.8 was chosen to be the most conservative but reasonable assumption.

In subsequent discussions with the University and changes to the project scope and budget, the sample size decreased to 25 and then 20 buildings, with relative precision values determined to be 23% and 28%, respectively. Ultimately, the SDSEP was prepared using energy models develop for a sample of 20 buildings.

Table 3 shows the cut points for z_i chosen for the population of buildings. As expected, each strata has progressively fewer buildings as the uncertainty of each building increases with z_i. The inclusion probability shows the percent probability of each building in that strata being chosen. The inverse of the inclusion probability will be the weight applied to each sample point when post stratifying.

Stratified sample design uses knowledge about the population to add efficiency to the sample design. A stratum is any subset of the projects in the population that is based on known information. A stratification of the population is a classification of all units in the population into mutually exclusive strata that span the population. Under a stratified sample design, simple random sampling is used to select a chosen number of projects from each of the established strata.

Added notation is needed to discuss stratified sampling. Let L denote the number of strata and assume that the strata are labeled h=1, 2, etc. Let N_h be the total number of population projects in stratum h. Let n_h be the number of projects to be randomly selected from stratum h . Assume that n_h is greater than zero for each stratum h . Then $\sum_{h=1}^{L} N_h = N$, the total population size, and $\sum_{h=1}^{L} n_h = n$, the total sample size.

Using this notation, the stratified ratio estimator can be defined. For each building i in the sample, the case weight is defined according to the equation $w_i = N_h / n_h$ where h denotes the particular stratum that contains building i. Using the case weights, we can define the stratified ratio estimator, denoted b, as follows:

$$b = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i x_i}$$

Table 3: Strata Cut-points and Sample Distribution (Initial 35 Building Sample Size)

STRATUM	*Max* z_i	POPULATION	SAMPLE	INCL. PROB
1	7,773,693	98	8	8%
2	15,891,699	37	7	19%
3	32,988,368	22	7	32%
4	58,527,890	13	7	54%
5	146,678,697	6	6	100%

The statistical precision of b can be assessed by calculating the standard error using the following equation:

$$se(b) = \frac{1}{\hat{X}} \sqrt{\sum_{i=1}^{n} w_i (w_i - 1) e_i^2}$$

Where $\hat{X} = \sum_{i=1}^{n} w_i x_i$ and $e_i = y_i - b x_i$. Then, as usual, the error bound can be calculated as $eb(b)$=1.645$se(b)$ and the relative precision can be calculated as $rp=eb(b)/b$.

The Ratio Model

To develop a suitable sample design, it is necessary to characterize the relation between x and y in the population. This is done by assuming a statistical model called the ratio model. The primary equation of the ratio model is $y_i = \beta x_i + \varepsilon_i$. Here x_i and y_i denote the value of x and y for each project i in the population, β is an unknown but fixed parameter of the model that is similar to a regression coefficient, and ε_i is similar to the random error in a regression model. As in a regression model, the expected value of ε_i is assumed to be zero for each site i in the population. It is also assumed that ε_i, K , and ε_N are mutually independent. Then μ_i is defined to be the expected value of y_i given x_i. Under the ratio model $\mu_i = \beta x_i$.

Instead of assuming that the standard deviation of ε_i is constant, the standard deviation of ε_i is allowed to vary from site to site. For any project i in the population, the standard deviation of ε_i is denoted as σ_i. This is called the residual standard deviation of project i. The population error ratio of x and y , denoted er , is defined

$$er = \frac{\sum_{i=1}^{N} \sigma_i}{\sum_{i=1}^{N} \mu_i}$$

The error ratio is the key measure of the population variability in the relationship between x and y for stratified ratio estimation. The role of the error ratio in stratified ratio estimation is virtually the same as the role of the coefficient of variation in simple random sampling. Figure 1 shows several examples of error ratios ranging from 0.4 (a relatively strong relationship) to 1.0 (a weak relationship).

The following specific functional form for σ_i is often assumed: $\sigma_i = \sigma_0 x_i^{\gamma}$. This is called the secondary equation of the model. The secondary equation specifies that the residual standard deviation of each project i in the population is proportional to the value of x_i raised to the power γ, commonly assumed to be 0.8. This specification is used in constructing efficiently stratified sample designs and to assist in the estimation of the error ratio from a prior sample. The secondary equation includes a parameter denoted σ_0 . This parameter is determined by the error ratio as follows:

$$\sigma_0 = \frac{\sum_{i=1}^{N} \mu_i}{\sum_{i=1}^{N} x_i^{\gamma}}$$

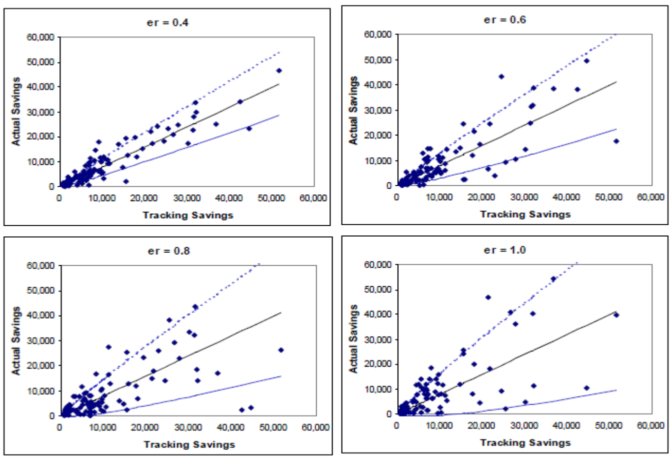

Figure 1: Examples of Error Ratios

We've discussed the concept of repeatedly selecting a random sample of a fixed size from a fixed population, observing the value of a particular variable y for each sample project, and calculating appropriate statistics. This concept can be used to define the sampling distribution of a statistic such as the sample mean. This same concept of repeated sampling is used in the present discussion of ratio estimation with one extension. Instead of regarding y_i as fixed for each project i, y_i is assumed to vary randomly from sample to sample, generated by independent realizations of the ratio model. In other words, the sample is regarded to be randomly determined following the prescribed sample design, and the true values of are y_i considered to be randomly determined for all N units in the population following the ratio model. (Sarndal et al. 1992)

Model-Based Stratification

This section will describe how the project team constructed an efficiently stratified sampling plan. The goal was to group the buildings into several strata based on the value of x, the estimated energy savings, and then specify the number of sample projects to be selected from each stratum. The following method is called model-based stratification by size.

1. Create a database listing each building in the population and provide the value of x_i for each building.
2. Use the assumed secondary equation for the ratio model to calculate σ_i for each project. The value of σ_0 can be assumed from the value of the error ratio assuming γ is set to 0.8. Sort the list of buildings by increasing σ_i. Calculate the cumulative sum of the σ_i, $c_i = \sum_{i=1}^{N} \sigma_i$
3. Choose the desired number of strata L, and divide the projects in the sorted list so that the sum of the c_i is approximately equal in each of the strata.

Once the strata have been constructed as just described, the sample should be allocated equally to each stratum. If the sample size in a particular stratum exceeds the population size in that stratum, the buildings in that stratum should be selected with certainty. If desired, the sample may be increased in the remaining strata so that the sample size is closer to the planned value.

In some applications, it may be desirable to stratify the population by a categorical characteristic of the projects as well as by size. For example, the projects might be stratified by building type, technology, contractor, or region. The underlying principle is that the sample size allocated to each categorical stratum should be proportional to the sum of the σ_i within each stratum. Given the definition of the error ratio, a convenient way to determine the sum of the σ_i within each stratum is to multiply the expected actual savings in each stratum by the error ratio assumed in the stratum. This gives the rule: the sample size allocated to each categorical stratum should be proportional to the product of the expected actual savings in each stratum and the error ratio assumed in the stratum.

Once the sample size has been determined within each categorical stratum, the projects within each stratum should be further stratified by size as described above. Using various sample sizes, it is then possible to determine the estimated relative precision of each, allowing for selection of a sample size that is appropriate for the desired level of confidence in the outcome. Table 4 shows the 20 building sample set finally selected to be modeled.

Table 4: Final Sample Set

	NAME	STRATUM
1	1700 Martin	1
2	Lenoir Building	1
3	General Storeroom	1
4	Ehringhaus Residence	1
5	Ram Village	1
6	Kerr Hall	2
7	Sitterson Co	2
8	Tate, Turner	2
9	Knapp-Sander	2
10	Administrative Bldg	2
11	Max Chapman	3
12	Fordham Hall	3
13	Taylor Hall	3
14	Davis Library	3
15	Michael J Ho	3
16	Morehead Chem	4
17	Thurston-Bow	4
18	Kenan Lab	4
19	Lineberger C	4
20	Jones F.L.O.	5
Estimated Relative Precision = .2775		

PHASE II - AUDITING AND MODELING

Audit Process

The auditing process for the project, while time consuming, was much more straight-forward than the statistical methods used to arrive at the final sample set. The 20 buildings were audited to a level consistent with what ASHRAE would deem a “Level 3” energy audit. (ASHRAE, 2011) Before the buildings were visited physically, drawings were collected along with 2 years of utility data. The physical audits were very detailed, with data collected on the state of equipment, deviations in the building from the UNC drawing sets, and known building problems. Surveys were also given to the operations staff; these included questions related to occupancy patterns and scheduling, equipment that was broken or disabled, temperature setpoints, and other issues. With audits completed, the project team began the modeling effort aimed at determining the energy savings of various measures for the sample set.

Utility Data Manipulation

UNC personnel made it clear to the team that not all of the utility data was reliable. Certain buildings in the sample had been closed for repairs and maintenance, while others had known problems with metering. The most common problem was utility data from manually read meters. The project team wanted to develop a typical monthly utility rate per building for each fuel from the years of provided data, and the manually-logged data did not always cover a single month, and it was often recorded in the middle of a month.

The modeling team adjusted the utility data to make the energy model calibration effort more straightforward. Rather than using a statistical normalization technique, this process involved adjusting the manually recorded data and splitting it out to calendar months. UNC staff were questioned about periods when the buildings were not in use or when the meter was known to be in error was removed. This was an intuitive and iterative process involving close coordination with UNC personnel responsible for building metering and utilities. While such an effort does introduce inaccuracies into the modeling process, it was an unavoidable part of moving forward, and the benefit of estimating savings with models calibrated with user input far outweighed any error introduced by composing and harmonizing campus utility data into a usable format.

Energy Modeling and Calibration

The 20 buildings within the sample set were modeled using the eQuest energy modeling software. This tool provided the best combination of speed, flexibility, and the ability to handle models with many dozens or hundreds of zones. While energy modeling is not the focus of this paper, the process used for the SDSEP will be described briefly.

As a first step, the project team set targets for accuracy between the metered data and the energy models of +/-5% difference on a monthly basis, and +/-10% difference on an annual basis. Energy models were built using detailed blueprints provided by UNC and marked with important information by the auditors. A high level of zone specificity was used, with many individual rooms and space being modeled, rather than being joined into “thermal blocks”. This was done to account for the unique pieces of equipment, specific airflow requirements, and unusual occupancy patterns observed by the auditors.

With 20 energy models generated, the project team set out to calibrate the models based upon data collected in the audits. Initially, all audit-related information was placed into the energy model input assumptions. For certain buildings, this initial data was sufficient to move the model into desired accuracy range. Other models did not meet the desired level of accuracy after the initial calibration effort, so further effort was warranted. A dialogue was developed between the energy modelers responsible for each building and UNC personnel familiar with that facility. Discrepancies between actual and predicted data were openly discussed, and this detailed interaction helped to mold the remainder of the calibration effort. A few examples of these many issues are as follows;

1. Staff determined which building economizers were actually functional vs. fixed in a set position
2. UNC determined the steam conversion losses between the main steam lines and building hot water systems
3. Unusual equipment, such as manually-controlled demonstration fume hoods for chemistry instruction, or kitchen equipment, were more accurately accounted for in the models
4. Previously unknown conditions, especially poorly performing VAV terminals, were diagnosed and added to the models

This effort not only brought all of the models into the desired accuracy range, but it helped to identify some of the major issues the campus faced in terms of building maintenance and possible measures for investigation moving into the final phase of analysis.

Energy Conservation Measure Analysis

With the project effort primarily focused on helping UNC personnel understand whole-campus energy savings potential, a series of energy conservation measures (ECMs) were developed. These ECMs were developed in conjunction with UNC, and were arrived at by looking at the findings of audits and calibration process, UNCs own internal conservation programs, and known deferred maintenance projects. 22 distinct ECMs were developed for the SDSEP, and the team

Table 5: ECMs Analyzed as Part of SDSEP, Broken into Grouping Categories

ECM	DESCRIPTION
Grouping 1: No Cost and Low Capital Investment	
1	(Setback): Day vs. Nighttime Temperature Setpoints
2	(Seasonal Differentiation): Summer vs. Winter Temperature Setpoints
3	(VAV Terminal Minimum Position): Reduced to 30% Flow
4	(HVAC Scheduling): Allows Units to Cycle On/Off at Night
5	(Lighting Scheduling): Utilize BAS-Programmed Lighting Sweeps
6	(Simultaneous Heating and Cooling Solutions): Preheat Control Correction
7	(Economizer Dampers Re-enabled and Set-point Recalibration to 65F)
8	(Supply Air Temperature Reset: 3F Higher Based on Zone Feedback
9	(Laboratory Airflow Reduction): VAV Labs Reset to 6 ACH Min.
Grouping 2: Mid Level Capital Investment	
10	(Lighting Upgrades): T12 to T8 Conversion
11	(Conversion to Task/Ambient Lighting): Lower Installed Wattage
12	(Occupancy Sensors): Occupancy Sensors Inform Lighting Control
13	(Daylight Sensors): Allow for Dimming of Lights with Sufficient Daylight
14	(VAV Full Shut-off): Minimum Position Reduced to 0% When Unoccupied
15	(Outside Air Variation with CO2 Sensors): Control OA Based on Occupancy
16	Variable Frequency Drive Fan Conversion
Grouping 3: High Level Capital Investment	
17	Full CAV to VAV System Conversion
18	(VAV Fume Hoods): CAV to VAV with 6 ACH Min. Setpoint
19	(Fume Hood Removal); 20% Hood Reduction with 6 ACH Min. Setpoint
20	(Water Source Heat Recovery Chiller): Provide Simultaneous HW & CHW
21	(Heat Recovery): Enthalpy Wheel or Run-Around-Loop
22	(Supply Air Static Pressure Reset): Reduced Fan Power

determined that each ECM should modeled as stand-alone as well as part of a grouping of similar scale ECMs. In this way, the merit of each measure could be demonstrated while also showing the interactive effects of applying multiple ECMs as part of a larger deployment strategy. The 22 ECMs chosen by UNC and the project team are shown in Table 5.

As part of the SDSEP process, the specific details regarding each of the 22 ECMs were developed to meet UNC expectations and guide cost estimating exercises for those ECMs UNC might chose to pursue. Detailed descriptions for each ECM were provided along with discussion of how ECMs could be deployed for different space and building types. When modeling the ECMs, care was taken to not model them in a way that would not be possible due to existing building requirements or specific conditions. For this reason, not all of the ECMs were modeled for each building (e.g. VAV fume hoods were not modeled for non-lab buildings or those labs already equipped) and minor alterations to some ECMs were necessary (e.g. setpoint schedules for academic buildings vs. residences and dining). This variation is acceptable because it mimics the outcome of an actual deployment of these ECMs throughout the UNC Chapel Hill campus.

ECM groupings were also modeled to demonstrate interactive effects. Each grouping (Low, Mid, and High Capital Investment) was modeled separately as well as in a final combined scenario with all potential ECMs for the building being analyzed together.

Unique to this effort was the use of a proprietary tool developed by (removed for review). This tool, known within the project team as the 'Space Load Processor', was developed to parse data from eQuest simulationsat each time step in order to determine energy use not only on a building level, but on a space-type basis as well. Using this technique, it was possible to determine how the savings of each ECM would be portioned out to each space type within a building. The space load processor was developed with multiple error checking features, and all results were compared against eQuest simulations not running the proprietary tool in order to ensure consistency of results.

Cost Estimating

High level cost estimating was also conducted for each ECM on a building-by-building basis by a team of experienced cost estimators. This effort generally used $/sf values for the deployment of each ECM, corresponding to the level of estimating typically done in the initial phases of project design. Costs were also developed for each building that would require an upgrade to a DDC style control system.

SDSEP PROJECT RESULTS

With energy savings, energy cost avoidance, and first cost information developed for each of the 20 buildings within the sample set, it was possible for the project team to use the statistical techniques outlined previously to begin extrapolating energy savings back out to a whole-campus level.

Results

As shown in Table 6, low capital investment ECMs, including strategies such as set-point changes, schedule modifications, and simple air change rate reductions, offer a savings of 17.5-22.5%. Low capital investment combined with mid capital investment payback measures such as lighting control upgrades and demand control ventilation could save 19-27% of the base energy consumption. Including the high capital investment ECMs such as heat recovery technology, raises the savings potential to 32-42%. The energy savings are not uniform across all utilities; 40% of the overall energy reduction results from steam reduction, 45% from chilled water, and only 15 % from electricity. Most of the electrical energy conservation potential is associated with mid capital investment payback ECMs that are extensions of current lighting system upgrades.

The potential economic implications are also shown in Table 6. The capital costs are based on extrapolation of estimated costs for ECMs associated with each of the 20 buildings. The energy cost avoidance estimates are based on the utility rates provided by the University.

Table 7 provides energy savings potential related to the six space type categories. The impacts of ECM groupings and combinations of groupings were shown to UNC in order to depict how interactions of ECMs can reduce the contribution of any one cluster.

The results of the Strategic Demand Side Energy Plan indicated that there was significant opportunity to reduce energy consumption on the UNC Chapel Hill campus by as much as 37%, and reduce energy consumption costs by approximately $22.5M annually through building improvements alone. The SDSEP was intended to give the University the investment confidence to leverage energy cost savings against the implementation costs of energy conserving measure deployment.

In addition providing an overall savings potential estimate, the SDSEP provided the University with the analytical tools used and output data developed for any further investigation and study. The calibrated energy simulation models for the twenty surveyed buildings were provided to UNC as tools for studying future ECM options, for ongoing assessment of building performance, or, perhaps, for adaptation to represent other buildings no included in the audit process. In addition to the models, complete sets of the output and cost estimation data were provided. These data will provide UNC staff the ability to update and modify capital investment cost and cost avoidance estimates as more detailed information becomes available and utility rates are altered. Commitment beyond the scope of the SDSEP analysis can be informed by the data provided and can assist the University in meeting the energy and carbon reduction goals.

Table 6: Projected Campus Energy Savings

	CURRENT	GROUP 1 ECMs	GROUP 1 & 2 ECMs (COMBINED)	ALL ECMS
ENERGY USED *(MMBTU/yr)*	2,640,000	2,110,350	2,024,000	1,658,350
ENERGY SAVINGS *(MMBTU/yr)*	--	529,650 ± 12.7%	616,000 ± 16.7%	981,650 ± 13%
ENERGY SAVINGS *($)*	--	20% ± 2.5%	23% ± 3.8%	37% ± 4.8%
CAPITAL COST *($)*	--	$2,320,000	$30,763,000	$50,480,000
ENERGY COST AVOIDANCE *($/yr)*	--	$5,207,000	$14,245,000	$22,627,000

Table 7: Energy Savings of ECMs by Space-Type (kBTU/sf-yr)

	GROUP 1 ECMs	GROUP 2 ECMs	GROUP 3 ECMs	GROUP 1 & 2 ECMs (COMBINED)	ALL ECMS
GENERAL & STUDY*(GS)*	26.3	14.4	7.6	34.2	39.0
RESEARCH LABS *(RL)*	213.4	7.9	397.9	156.0	480.1
TEACHING LABS *(TL)*	257.4	146.8	430.4	292.5	504.8
OFFICE*(OF)*	134.2	100.8	73.5	179.1	218.3
RESIDENTIAL*(RF)*	30.5	19.1	0.0	46.8	46.8
SUPPORT & SPECIAL*(SS)*	33.6	11.6	6.6	37.4	41.7
OTHER*(OTHER)*	39.1	16.6	56.0	47.3	91.1
TOTAL	455.7	278.3	510.5	558.8	811.6

ONGOING RESULTS & REAL-WORLD PROGRESS

The majority of the work associated with the SDSEP project was completed and delivered to UNC in 2009. Since then, the Energy Management Office of the UNC Facilities Services division has been engaged in an effort to deploy a variety of low capital cost ECMs (most coming from the Group 1 ECMs described in the SDSEP). (University of North Carolina, 2011) Seven energy conservation measures were given priority by the Energy Management Office, with a small team created to facilitate thorough deployment across the campus. These seven strategies and their SDSEP ECM counterparts are listed as follows:

1. Supply Air Temperature Reset: 3F Higher Based on Zone Feedback (ECM 8)
2. Implement HVAC Unoccupied Setbacks and Shutdown (ECM 4)
3. Change minimum cooling airflow set points (SDSEP ECM 3&9)
4. Identify and eliminate simultaneous heating and cooling (ECM 6)
5. Implement temperature standards: Summer 76F-78F, Winter 69F-71F (ECM 1 & 2)
6. Enable all heat recovery loops and economizers (ECM 7)
7. Enlist campus community to shut off lights and equipment (ECM 5 & 12)

The Energy Management Office is a working part of UNC Facilities Services, and verification of the modeling and statistical approaches of the SDSEP is not of critical importance to them. Long term tracking of the applicability of the statistical analysis is not currently formalized, so it will be difficult to gauge the accuracy of the SDSEP effort in predicting the occurrence of individual issues, such as simultaneous heating and cooling.

Data collected by the UNC Energy Management office beginning in 2009 shows that the deployment of ECMs across the campus has saved approximately $12M as of the beginning of 2012. Unfortunately, it is not possible to determine what portion of these savings can be attributed directly to the SDSEP due to the aggressive pursuit of unique ECMs and other measures not presented within the SDSEP analysis. Figure 2 shows the latest data published by UNC outlining monthly savings for the first half of the 2012 fiscal year and the cumulative savings of the project since deployment in August 2009. All values have been normalized for weather conditions by the UNC Energy Management Office. Figure 3 shows the weather normalized monthly savings of the ECM program for fiscal years 2011 and 2012 (all data provided by UNC).

FINAL THOUGHTS

While large-scale efforts like the Strategic Demand-Side Energy Plan prepared for UNC are not always the best approach to treating institutional energy savings programs, it does provide a unique framework for developing estimates for energy savings for any collection of buildings. Those who are seeking to use this framework must understand that even with the time-saving benefits of statistical techniques, this is not a simple or expedient process. It is often easier to make investments based upon high-level audits of existing buildings than to attempt to predict the energy savings of an entire campus, but there are situations where such broad understanding is required.

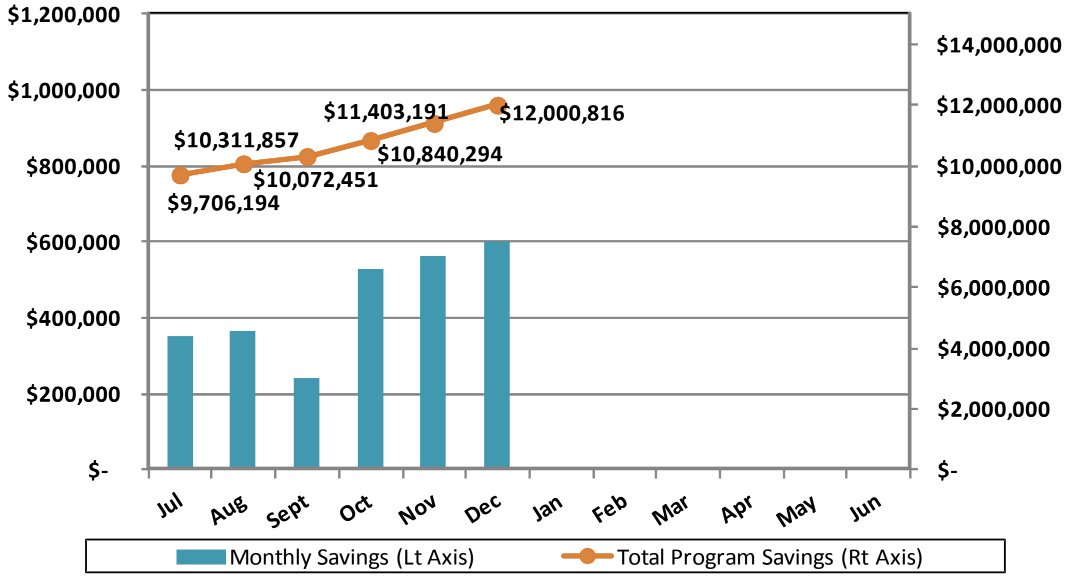

Figure 2: Monthly and Cumulative Avoided Costs for ECM Buildings - Weather Normalized (Provided By UNC Energy Management)

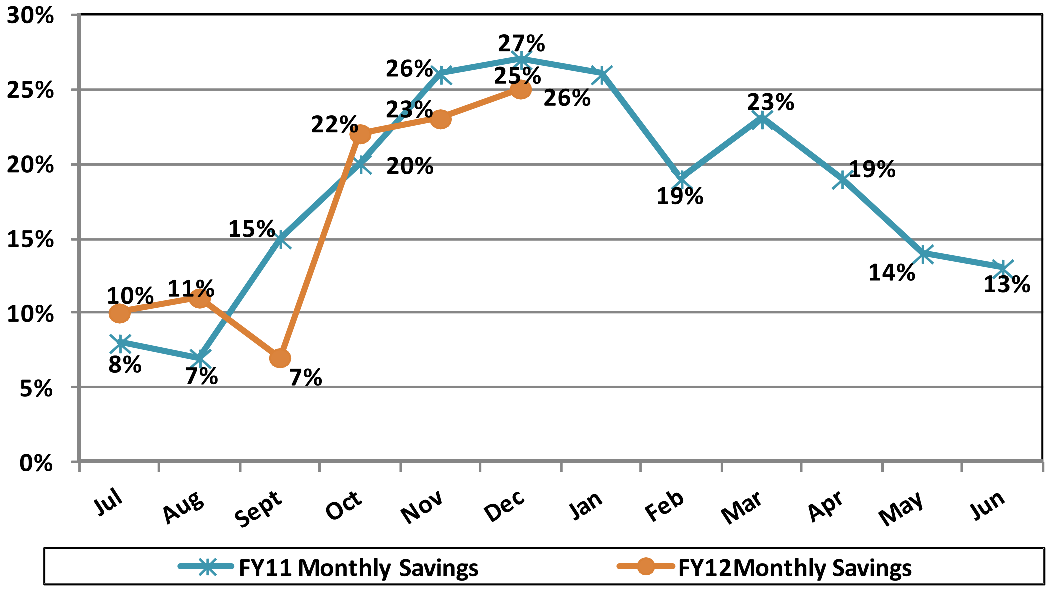

Figure 3: Monthly Savings - Weather Normalized (Provided By UNC Energy Management)

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