NET ZERO ENERGY RETROFIT USING CALIBRATED MODEL, OPTIMIZATION TECHNIQUES AND REGRESSION GRAPHS

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ABSTRACT
Optimization techniques and methods for selecting better solutions (as defined by the metric chosen) are becoming more common in simulation software. Several methods are available for energy consumption optimization: parametric analysis, genetic algorithms, and examination of alternatives via the Pareto front. Optimization algorithms and design alternative methods, as offered in commonly used energy software programs, offer techniques for guiding designers towards “better” (less energy use) solutions. Processes for incorporating these existing tools into a designer’s workflow needs to be examined, critically evaluated, and improved.

This paper attempts to bring concepts primarily used in research arena to be part of sustainable consulting workflow on retrofit projects. These concepts include calibration of energy models to existing building performance data, use of regression graphs and optimization techniques to evaluate potential energy efficient strategies for the project. The paper does not describe advancement of these topics in research and rather explains state of art workflow for energy consultants.

INTRODUCTION
According to a survey by the U.S. Energy Information Agency, seventy two percent of floor stock in the USA or forty six billion square feet, belongs to buildings over twenty years old. (EIA CBECS 2003, Table B9). These older buildings consume a lot of energy and there is a need to reduce overall energy consumption and increase its energy efficiency. The market is realizing the vast potential of retrofit opportunities and creating an environment that is comfortable, efficient and cost effective.

This paper describes a workflow using a retrofit case study of an existing institutional building of approximately 90,000 square feet that was built in 1960’s. The workflow is on the similar lines of an investment grade audit. An energy model was created for the building, calibrated to accepted error tolerance (as described later in the paper), and used optimization techniques to explore and evaluate various energy efficient strategies.

The whole building simulation model was created based on precise building geometry, occupancy, and equipment power and lighting densities using the Energy Plus engine with DesignBuilder as the interface. Building schedules were input to closely relate the digital model to the actual building’s use. This was done by monitoring of occupancy, heating, cooling, lighting and ventilation. Spot measurements for plug loads were taken and overlaid with occupancy to formulate plug load schedule used in the simulations. The HVAC system was modeled as per the drawings and air balance reports with relevant chiller and pump curves.

Energy signature graphs were created for case study building’s metered energy consumption and for that of energy model. This was used for systematic tuning of some modeling inputs (described later in the paper) to meet an acceptable level of calibration error for chiller energy consumption and whole building energy consumption. The CV(RMSEmonth) Coefficient of variation of the root mean squared error per FEMP (Federal Energy Management Program) M&V (measurement and verification) guidelines was accepted as tolerance level for the calibration of energy model. This meant that energy consumption predicted by energy model for every month has to be within ± 10% of metered energy consumption of the building.

After the model was calibrated, optimization techniques were used to determine several ‘optimum’ energy efficient solutions that would reduce both energy consumption and the capital cost of retrofit. The optimization techniques are based on an evolutionary algorithm that produced solutions that could be compared against the optimal Pareto front. By using this technique, it was possible to explore and experiment with different combinations of parameters using a robust energy analysis engine. The parameters for optimization included glazing films, internal blind types, shading types, HVAC system type, air distribution, lighting and control strategies. Solar photovoltaic panels could then offset the minimal energy required to operate the building.

PERFORMANCE BASED DESIGN: EXISTING TOOLS AND TECHNIQUES
In a “traditional” mode of analytical modeling, a digital model is constructed, and then performance
simulations are run. The modeller changes the model, creates another set of runs, and compares them against the base case. The feedback from the analysis informs the next set of runs. Another paradigm is for the software to not just supply a result of one calculation, but instead to help in either running of multiple parameters for analysis or “optimizing” the design for specific criteria. Several methods are available for doing optimization: parametric analysis (used as mentioned for directed goal finding), genetics algorithms, and the Pareto Front are discussed below in the context of software programs that use them for energy analysis.

**Parametric Analysis**

*Parametric analysis* is a well-established technique to discover a design with most favorable characteristics by systematically adjusting variables, usually only a few of them at a time. Parametric analysis can be performed with just one variable. It can be as simple as having a spreadsheet where the user methodically changes one value until another value reaches the targeted value. The example in Figure 1 shows a computerized version of understanding the impact of one variable (“angle” of brise soleil) in terms of annual energy consumption while keeping other parameters like “separation” and “depth” constant. The example shows that for a range of -45 to 45 degrees, the energy consumption is lowest for +-25 degrees.

![Figure 1: Use of Sefaira response curves to optimize the angle of a brise soleil](image1)

Another example of parametric analysis is to reduce energy consumption by understanding the correlation of any two variables. For example, correlation between window to wall ratio (WWR) and total energy consumption with different type of glazing types. These results are displayed as a series of parametric design curves calculated in DesignBuider (using the EnergyPlus engine). The design curves gives options for the designer up front to analyze and choose a WWR coupled with glazing types based on both aesthetics and performance (Figure 2). Note that the designer is not being coerced into choosing a single solution but is learning the consequences of different choices.

![Figure 2: Parametric curves illustrating effect of different WWR and glazing combinations on energy consumption](image2)

Although not technically an optimization technique, another way to understand sensitivity of different variables is the use of sensitivity graphs. The New Building Institute (NBI) has published a report that includes the impact of different variable in different climate zones by using an energy model to predict energy consumption (Heller et al. 2011). This is an incredible resource to understand which variables play an important role in a specific climate zone and should be targeted first to reduce overall energy consumption. These variables are divided into six main categories: envelope, lighting, HVAC, operations, occupancy, and other.

Figure 3 shows impacts of variables in Climate Zone 5B (Denver, CO). The bar below 0% (green) shows how much energy can be saved from that particular variable as compared to a typical building. The bar above 0% (orange) shows how much penalty can be accrued from that variable. The height/magnitude of the bar indicates the sensitivity of variable (bigger bar height means it is more sensitive and has higher energy impact potential).

![Figure 3: Sensitivity analysis for CZ 5B, source: NBI](image3)

There are limitations in finding optimal solutions using parametric analysis, for example, the number of variables that can be practically explored with single optimization objective (e.g. best comfort, low energy consumption etc.) (DesignBuilder v4.3, 2015).
Genetic Optimization

Another form of optimizing techniques uses genetic or evolutionary optimization algorithms to explore locally optimal design solutions (Coello et al. 2007). This can be a more efficient way to find optimal designs depending on the problem and can solve for multiple conflicting objectives, for example, minimizing energy consumption while maximizing comfort levels or minimizing loads while also minimizing life-cycle costs. These are also called multiple objective optimizations.

DesignBuilder uses a Genetic Algorithm (GA) based on the NSGA-II method, which is widely used as a “fast and elitist multi-objective” method providing a good trade off between a well converged and a well distributed solution set. It works as follows:

- First, the population is randomly initialized.
- Chromosomes (design variants) are sorted and put into fronts based on Pareto non-dominated sets. Within a Pareto front, the chromosomes are ranked based on Euclidean distances between solutions or I-dist (term used in NSGA-II). Generally, solutions which are far away (not crowded) from other solutions are given a higher preference in the selection process to help create a diverse solution set and avoid crowding.
- The best designs are picked from the current population and put into a mating pool.
- In the mating pool, tournament selection, crossover and mating is carried out.
- The mating pool and current population is combined. The resulting set is sorted, and the best chromosomes are passed into the new population.
- Go to step 2, unless maximum number of generations have been reached.
- The solution set is the highest ranked Pareto non-dominated set from all populations.

(DesignBuilder v4.3, 2015)

Pareto Front

Building level optimization can be done in several software programs. In this research, the DesignBuilder’s optimization module is used to find an optimal solution for multiple objectives that are of interest to the designer, but may be in opposition to each other, for example, minimizing energy demand normally leads to increasing capital cost. It addresses multiple objectives that are defined in the software and also deals with constraints to that optimization objective (e.g. minimum day-lighting criteria to meet, limited capital cost, discomfort hours allowed, etc.). Pareto Front shows the optimized solutions (Figure 4). The Pareto front is the set of solutions of the different weighting factors. The solution graph might include the entire set of points tested (the parametric analysis) that meets the objectives and satisfies the constraints creates a feasible region defined by the input constraints. The set of points that bound the bottom of the feasible region is the Pareto front (Haupt, R.L. and Haupt, S.E. 2004).

CASE STUDY

The Von Kleinsmid Center (VKC) is a landmark building at the University of Southern California in Los Angeles, CA (Figure 5). Built in 1966, it has a non-occupied prominent brick tower and three-story brick blocks in a U-shape around a central exterior courtyard. The total area of 90,287 sf is distributed in a library in the basement, classrooms on the first and second floors, and offices in the upper floors.

Energy Model: Engine

Energy Plus engine, which is widely used engine in industry and has been recognized for its accuracy and flexibility of modeling high performance strategies was used in this research. It uses an integrated simulation methodology that solves for heat and mass balance for each surface and calculates space loads and building systems simulation at the same time step. “Zone,” “system,” and “plant” talk and provide feedback to each other for each time step of the simulation. An energy balance equation is written for each enclosing surface in addition to an equation for room air that allows the net instantaneous sensible load to be calculated for space air. (Wadell and Kaserekar 2010)

Energy Model: Weather Data

Real weather data for 2010 in EPW format was obtained from the KCQT weather station, latitude 34.0511 degrees north, 118.235 degrees west, in downtown Los Angeles. This is approximately three miles from USC. According to that weather data, September 27st was the hottest day in 2010 with a maximum temperature of 106.8°F at 5 pm, and December 31st at 2 pm the coldest with a temperature of 37.1°F. Winds are generally from the south west and west directions with wind temperatures varying from 32°F to 75°F.

Energy Model: Geometry

The geometry was created in Revit and then exported to simulation model via gbXML. Minor adjustments were done for basement courtyard and adjacency set to ‘outdoor’ instead of default ‘ground’. (Figure 5)
Energy Model: Site Surroundings

Shadow analysis were done for the month of March, June, September and December to understand the impact of neighboring buildings on VKC. (Figure 6).

Energy Model: Building Components

Walls (sub-grade and exposed), slabs (sub-grade and internal), roof, and finishing materials had been matched using the U-values and dimensions as per the architectural drawing set and dimension verification in the field. Table-1 shows these properties along with glazing properties that were used in simulation.

<table>
<thead>
<tr>
<th>ITEM</th>
<th>PERFORMANCE VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roof</td>
<td>R-6.27, U-0.16</td>
</tr>
<tr>
<td>Above Grade Wall</td>
<td>R-3.47, U-0.29</td>
</tr>
<tr>
<td>Below Grade Wall</td>
<td>C-1.140</td>
</tr>
<tr>
<td>Ground Floor</td>
<td>F-0.73</td>
</tr>
<tr>
<td>Glazing</td>
<td>SHGC-0.62, VLT-0.7, U-0.9</td>
</tr>
<tr>
<td>Doors</td>
<td>U-0.7</td>
</tr>
<tr>
<td>Airtightness</td>
<td>0.7 ACH</td>
</tr>
</tbody>
</table>

The roof is flat aggregate and covered with an asphalt application. The structure of the building is reinforced concrete and steel with a brick veneer. Interior partitions are painted sheetrock distributed in a grid of concrete columns. Floor finishes vary among spaces, with vinyl in the library and classrooms and carpet in the offices. Ceilings are a combination of acoustical tile and textured sheetrock.

Energy Model: Zoning, room use, and schedules

The building’s basic functions are library, classrooms, computer rooms and offices (Figure 7). Unconditioned areas account for 11% of the total area of the building and include mechanical rooms, restrooms, and access areas. The library is located in the underground area where daylighting is provided by the central courtyard through a fully glazed perimeter. Classrooms are located in the east and west blocks and are of two types, older traditional classes and new classrooms. The latter have been equipped with modern controls for occupancy and equipment, which resulted in different schedules having to be input. Offices are located in the second floor of the north block and the entire third floor. There are two computer labs, located on the second floor and third floor.

All schedules for occupancy, lighting, and equipment were input into the energy model. The occupancy schedule was obtained from the classroom scheduling office at USC. Equipment usage within the class is not directly proportional to the number of classes and their duration. For example, not all classes use the audio-visual equipment. A recorded list of equipment usage was obtained from Information Technology Services (ITS) department at USC. This department keeps a log when the equipment is used and for what classes. This was helpful to determine the intermittent load for classrooms. The HVAC schedule was obtained from Facilities Management Services at USC for both school year and summer hours of operation.

Energy Model: HVAC

The building is conditioned with four air-handling units (Figure 8). Infrastructure steam feeds a heat exchanger that generates hot water for heating. Steam condensate is handled by one central accumulator/return system. Hot water is circulated to air handler coils for preheat and primary heat. Hot water is also circulated to reheat terminals.
The HVAC distribution for AHU-3 had migrated to a variable volume design whereas AHU-1 and AHU-4 were still operating with dual duct air-distribution system with pneumatic controls.

The building had two Trane’s Centravac Rotary Liquid Chiller Model RTHA-180 (long shell) of 160 tons cooling capacity. A detailed 15 min interval data is obtained from the building management system in addition to chiller curves for use in the simulation.

**Calibration of Energy Model**

All building information gathered for envelope, HVAC, lighting, equipment, schedules were input into the energy model. Load calculations were done and verified against the rules of thumb and manual calculations. The rules of thumb were 400 sft/ton of cooling capacity, 20-30 btu/sft of heating capacity. Once auto sizing was in the ballpark area, all inputs were hard sized per actual values.

An energy signature graph (Figure 9) was created for VKC metered energy consumption to understand the pattern and co-relation with outside conditions to the energy consumption.

**Figure 9: Energy signature graph of metered consumption**

This is based on inverse modelling technique in which energy use drivers are identified first leading to statistical model and then fine-tuning of building parameters. The VKC energy signature graph includes following:

X-Axis: average temperature of the month  
Y-axis: energy consumption  
\[Tcpc = \text{change rate (balance temperature of building)}\]  
\[CS = \text{cooling slope (Kissock, K et al 2008)}\]

As per the metered energy signature of VKC, it was clear that the balance point for this building is 62.5°F and base load of the building was around 6.5 watts per square foot per hour. The graph also identifies a metered cooling and heating slope of the building.

If the design and operational parameters don’t change, then the energy consumption can be predicted for any month (Kissock, K et al 2008). Energy signature graph made it possible to do targeted calibration using graph as pointers. This graph was made for base energy model that was then compared to metered energy signature graphs to identify areas that need to be further calibrated. The insights that were obtained varied from base load difference, heating/cooling efficiency & schedules and difference in balance point of the building. This process was repeated for subsequent iterations of energy model, which helped immensely in the calibration process.

The energy model peak demand (kW) was first targeted to match actual peak demand of the building. Following which energy use (kWh) was calibrated. The chiller electrical consumption is a large component of overall electricity consumption and was the first thing to be brought closer to actual metered consumption. Partial load curve was obtained from Trane for that specific chiller model and the coefficients were inserted in the simulation model. The detailed hourly amps, supply temperature, and return temperature values were obtained from Facilities Management Services. The power consumption of the chiller was calculated based on this information and compared to the power consumption estimated by the energy model.

The profile of both VKC chiller’s actual electrical consumption and energy model predicted consumption was quite close except in the month of April (Figure 10).
At this point, not all the ranges were within acceptable error \( \pm 10\% \) margin based on CV(RMSEmonth) Coefficient of variation of the root mean squared error but quite close. The profile of energy model predicted chiller consumption was then compared to the profile of outside dry bulb temperature (Figure 11).

![Figure 11: DB predicted chiller consumption and monthly outside dry bulb temperature](image)

Both the profiles exactly matched. The average monthly temperature increased in March, reduced in April, and then increased from May onwards. The electrical consumption predicted by the energy model is also following the same path. It was eventually found that an event (five day film shooting) occurred in April that had spiked up the electrical consumption in the building. This information was added to the energy model with increased plug loads, lighting power density and modified schedules for that period. This brought the simulation energy consumption very close to metered.

Once chiller demand kW and electrical consumption kWh was close to the actual consumption, it was found out that building’s peak KW in simulation was close to metered demand but slightly on the higher end. The only logical thing that could be creating this discrepancy was the plug loads. The equipment power density was reduced in select areas per discussion with classroom scheduling office. It made the building peak KW match simulation peak KW. The energy usage (kWh) of the building was still not fully calibrated. Once, night-time emergency lights and cleaning crew timings were incorporated in the schedule more carefully, the ranges got within acceptable error \( \pm 10\% \) margin based on CV(RMSEmonth) Coefficient of variation of the root mean squared error. Figure 12 shows the different simulations runs that were done to reach a calibrated model.

![Figure 12: Calibration runs](image)

The table 2 further describes the numerical values of comparison and CV(RMSE) error for each month.

### Table 2: Calibrated model errors

<table>
<thead>
<tr>
<th>Month</th>
<th>VKC Metered (kWh)</th>
<th>Calibrated Model (kWh)</th>
<th>CV(RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan'10</td>
<td>103.09</td>
<td>97.88</td>
<td>4.62</td>
</tr>
<tr>
<td>Feb'10</td>
<td>92.00</td>
<td>98.76</td>
<td>6.06</td>
</tr>
<tr>
<td>Mar'10</td>
<td>108.41</td>
<td>116.51</td>
<td>7.25</td>
</tr>
<tr>
<td>Apr'10</td>
<td>110.06</td>
<td>105.60</td>
<td>3.99</td>
</tr>
<tr>
<td>May'10</td>
<td>113.36</td>
<td>103.79</td>
<td>8.58</td>
</tr>
<tr>
<td>Jun'10</td>
<td>103.09</td>
<td>102.99</td>
<td>0.09</td>
</tr>
<tr>
<td>Jul'10</td>
<td>113.85</td>
<td>108.33</td>
<td>4.95</td>
</tr>
<tr>
<td>Aug'10</td>
<td>115.15</td>
<td>116.96</td>
<td>1.96</td>
</tr>
<tr>
<td>Sep'10</td>
<td>124.54</td>
<td>129.37</td>
<td>4.33</td>
</tr>
<tr>
<td>Oct'10</td>
<td>139.02</td>
<td>128.19</td>
<td>9.70</td>
</tr>
<tr>
<td>Nov'10</td>
<td>118.90</td>
<td>110.18</td>
<td>7.81</td>
</tr>
<tr>
<td>Dec'10</td>
<td>93.71</td>
<td>87.79</td>
<td>5.30</td>
</tr>
<tr>
<td>Total</td>
<td>1339.11</td>
<td>1306.36</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>111.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Deep Retrofit Targets**

Energy usage should be reduced through low-energy building technologies like day-lighting strategies, high-efficiency HVAC, natural ventilation, evaporative cooling etc., and only after those were optimized, should on-site generation be used. The project goals were based on Arch 2030 Challenge for the period of 2010-2015 (figure14). This meant 60% reduction in energy use compared to Commercial Buildings Energy Consumption Survey (CBECS). The energy use intensity target was set as 31 kBtu/sf-yr as theoretical minimum. However, keeping in mind that this is a retrofit project and has many limitations for pursuing numerous energy efficiency measures; the implementable target was set as 45kBtu/sf-yr.

![Figure 13: Calibrated model](image)

In order to achieve the implementable target for the project, optimization techniques were used to identify energy efficiency measures for this project.
Energy Efficiency Measures using Optimization

There were two primary objectives of optimization: minimize operational energy (in terms of carbon dioxide emissions) and minimizing renovation cost. The optimization was set with constraints on the number of uncomfortable hours (maximum 300). This meant that the simulations that had over 300 hours of discomfort per ASHRAE 55 were automatically excluded from the final set of solutions.

There were several parameters tested and optimized. The detailed list with their minimum and maximum values is shown in table-3. Several different types of HVAC systems were tested including VAV (variable air volume) with terminal reheat, fan-coil units, radiant floor heating with DOAS (dedicated outside air systems) with heat recovery, passive chilled beams with displacement ventilation, natural ventilation and air source heat pump with floor heating, and LTHW (low temperature hot water) radiators with natural ventilation.

<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Min Value</th>
<th>Max Value</th>
<th>Step</th>
<th>Options</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ext Wall</td>
<td>R-10</td>
<td>R-60</td>
<td>5</td>
<td>Building</td>
<td>Exteral Wall</td>
</tr>
<tr>
<td>Shading Type</td>
<td>R-20</td>
<td>R-60</td>
<td>5</td>
<td>Building</td>
<td>Shading</td>
</tr>
<tr>
<td>Glazing Film VLT</td>
<td>0.1 0.8</td>
<td>0.05</td>
<td></td>
<td>NS/E/W</td>
<td>Facade</td>
</tr>
<tr>
<td>Glazing Film SHGC</td>
<td>0.15 0.6</td>
<td>0.05</td>
<td></td>
<td>NS/E/W</td>
<td>Facade</td>
</tr>
<tr>
<td>HVAC System Type</td>
<td></td>
<td></td>
<td>10</td>
<td>Building</td>
<td>HVAC System</td>
</tr>
<tr>
<td>LPD</td>
<td>0.5 1.5</td>
<td>0.05</td>
<td></td>
<td>Perimeter</td>
<td>LPD</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td>4</td>
<td>Building</td>
<td>Controls</td>
</tr>
<tr>
<td>Ext Lighting</td>
<td></td>
<td></td>
<td>2</td>
<td>Building</td>
<td>Ext Lighting</td>
</tr>
</tbody>
</table>

Lighting control options that were tested included continuous dimming up to 10%, continuous dimming up to 0%, three stepped dimming and two stepped dimming. Exterior control options included time clock and time clock with override off in daytime. Options for shading type varied from different depths of exterior louvers, overhangs, side fins, internal blinds with reflectivity slats, internal roller shade, internal diffusing fabric blinds and electro chrome glazing.

Costs for upgrades were estimated based on mixture of sources. It was primarily based on research which included the line item cost, miscellaneous cost and regional adjustment factor embedded in cost module of DesignBuilder software. Other resources used were RSMeans Square Foot Costs 2014 and RSMeans Assemblies Cost Data 2014. (RS Means, 2014)

The optimization module calculated solutions based on the Pareto Front evolutionary algorithm. Optimal solutions in this case would be a best-retrofitted glazing film to maximize daylight yet reduce solar gains, cost effective insulation thickness for roof and walls. This solution would include optimized depth of exterior shading, lighting power density and lighting controls. Lastly, this solution will have right type and sizing of HVAC system and controls to reduce both operational energy and retrofit capital costs.

Nine hundred and eighty simulations were carried out based on maximum generation of 100 and maximum population size of 20 to get a set of optimized solutions. Out of these, designers can select the options and combinations that suit their overall design goals. For example, designer might select the most energy efficient solution for projects with higher budget or choose a solution which is a good bargain between energy efficiency and cost for that particular project.

Improved Energy Model

A final version of energy model was created using the learnings from optimization analysis. In this case, designer selected a mid-range option from the pareto front. This included R-35 roof, R-26 wall, 2.5’ horizontal shade for south elevation, addition of high performance films reducing SHGC to 0.2 and VLT to 0.6, vertical fins for east and west elevation along with internal blinds with reflected slats. Furthermore, lighting power density of 0.5 watts per square foot and continuous controls with fixture off capability. Exterior LED lighting with time clock and override capability during daytime. Lastly, an HVAC system with natural ventilation and evaporative cooling section in dedicated outside air unit. Radiant heating ceiling panels at perimeter zones.

Predicted energy use intensity, EUI, once these strategies were modelled came out to be 39 kBTU/sft-yr. This was within the implementable minimum goal decided for the project.

Renewables

A total of 367 racks could be placed on the roof each having 4 PV panels. Therefore, the power generating PV panels count is 1468. Each panels generate average 305 W, the DC rating of the system is 1468 x 305 = 447KW. (DC rating = No. of Panels x KW per panel).

NREL PV Watts was used to estimate that these panels
would generate 716,695 kWh annually. This is equivalent of energy use intensity of 27 kBu/sf-yr. Another array was recommended on the empty area on the south side of the building to have another 200kW of solar photovoltaic panels as a shading canopy. These two fields combined would be able to offset annual energy consumption of VKC building.

**CONCLUSION**

In summary, the measured energy use intensity, EUI, was reduced from 78.5 kbtu/sf-yr to predicted energy use intensity, pEUI, of 39 kbtu/sf-yr (48% reduction). This was within the implementable goal set for this deep retrofit project. Renewables are then supposed to offset this energy consumed to make this facility work as net zero energy on annual basis.

It must be understood that to reach this target, measurement and verification plan should be executed and on-going commissioning done to make sure things are working as retrofitted. Moreover, there is a need for occupant behaviour and expectations to be adapted for making this facility work as zero net energy facility.

What is critical for designers is not the amount of energy that was saved in this case study, but the integration of optimization process in the retrofit design process. The optimization process gives enough flexibility to the designer to choose what he considers as the optimal solution based on project constraints out of designs landing on the Pareto Front. Retrofitting a building intelligently involves first understanding how the building is currently performing, second creating a simulation model that behaves like the building, and third trying out different possible options by software to discover a useful set of possible retrofit strategies. Optimization tools can help makes this process easier for designers.

**LESSONS LEARNED**

These optimization tools are constantly developing, improving their optimization capabilities, and becoming more user friendly for designers. However, at the time of writing this paper, there were several limitation faced while using Design Builder’s optimization module. This also limited the outcome of optimization and less aggressive optimized results. Some of these included missing of HVAC systems like ground source heat pumps, variable refrigerant flow etc. in the HVAC optimization template which could otherwise be modelled in the software. ‘Step’ functionality of optimization was not properly working which meant there were more checkpoints and longer runs. ‘Daylight’ constraint is still in works and could not be used during optimization for this case study. This meant the fitness criteria of optimization could select a poorly lit while highly energy efficient combination. The author had used the local machine to run these optimization runs and had longer run times including leaving PC running overnight. However, cloud computing has been integrated as an option and can be used for faster analysis. There was no constraint option for unmet hours for the project. Hence, no direct way of confirming if the model had reasonable unmet hours from optimization results apart from running the annual simulation again by updating the model using the optimized parameters. Lastly, the software was crashing several time upon use of constraints option.

This paper primarily used inherent capital costs and operational energy in the form of carbon dioxide emissions to find an optimal solution. Even though it is based on underlying concepts of life cycle cost analysis (LCC), it is slightly different. Therefore, a detailed LCC analysis should be done to evaluate the options considered that includes incremental cost, economic triggers, rebates and tax credits (utility, state, historic, 179D, innovation) available for the project. Economic trigger in this case was not to invest in bigger size chiller to overcome comfort issues but to improve envelope and reduce loads of VKC and invest in alternate cooling techniques. Furthermore, a business case should be created that includes the value of retrofit beyond cost savings which includes the benefit of occupants productivity, healthy occupants, occupant retention and their comfort. Lastly different financing options should also be created. For example, commercial loans, capital or operating lease, Property Assessed Clean Energy (PACE), Energy Savings Performance Contract, Energy Service Company’s (ESCO) service offerings relevant to the project.

**REFERENCES**


RSMeans Square Foot Costs 2014, 35th Annual Edition

RSMeans Assemblies Cost 2014, 39th Annual Edition