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Maintaining Large Fleets of Energy Models of Existing Buildings

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ABSTRACT

Continuous maintenance of large fleets of building energy models (BEMs) is a new challenge that is approaching economic parity for large institutions. In the past, BEMs have mostly been used for analyses during design with little or no reuse of the model. The Energy Independence Security Act (EISA) of 2007 to complete energy and water evaluations for federal facilities is changing this. EISA requirements can be met through performance of ASHRAE energy audits that allow BEMs for identifying energy savings opportunities. Sandia National Laboratories developed a fleet of 121 BEMs for site-wide energy assessments that can also be leveraged for this purpose. Beyond EISA compliance, BEMs have the potential to be used for site-wide retrofit assessments, model-based energy analytics, and model predictive control. Even so, the necessity of maintaining different configurations of BEMs for several applications is a difficult and unsolved problem. The authors propose maintaining accuracy of the energy-use breakdown over the BEM fleet with a continuous maintenance process on a 4-year cycle where models are audited alongside their corresponding buildings. We have begun to address this through quality checks and the incorporation of auto-calibration. This paper outlines the first year of efforts to construct a streamlined process for quality assurance of energy-use breakdowns including efforts on the first 5 models to go through the quality check and auto-calibration procedure. ASHRAE Guideline 14-2014 was met by most but not all the buildings. Even so, significant improvements to modeling were achieved for all five buildings. The first BEM underwent both manual and auto-calibration for a direct comparison. Manual calibration incurred more cost and required more time from staff members. Auto-calibration required significantly less effort, slightly less cost, and resulted in slightly better accuracy. Many improvements to the processes used to prepare data and models have been identified including issues that require major changes to SNL's energy tracking infrastructure. Although further infrastructure development is needed, our efforts highlight methods that are making large fleets of BEMs profitable.

INTRODUCTION

Potential markets for Building Energy Models (BEM) are expanding and rapidly changing (Hong et. al., 2018). This includes en-masse use of BEM on existing buildings (Villa et. al., 2017). Meanwhile, existing energy efficiency practice's profitability may be slowing (Stuart et. al., 2018) and may benefit from innovative uses of BEMs. Many efforts are underway to automatically generate entire campuses and cities through urban-scale building energy modeling techniques (Nagpal and Rienhart, 2018; ORNL 2018; NREL, 2018; Chen et. al., 2017; Reinhart and Davila, 2016) yet such efforts have not spanned the gap between generalized energy consumption for groups of similar buildings and prediction of operational performance for individual buildings. The level of detail needed by large commercial institutions is higher fidelity and includes proprietary data sources. Institution-scale research efforts therefore require focus on the maintenance of large fleets of BEM that leverage automation but allow efficient manual intervention to achieve accuracy where automation techniques are still undeveloped. As developments unfold, automation will be able

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to be applied to areas such as HVAC systems, occupancy, and internal loads.

Sandia National Laboratories (SNL) created 121 DOE 2.2 BEM from 2012 to 2017 for site-wide assessment of energy conservation measures (ECM). The results of these analyses were used to estimate the feasibility of institution-side energy efficiency goals (Villa et. al., 2017). These site-wide assessments are only needed every couple of years. One new application starting in 2018 has been using the fleet as a resource for compliance to the Energy Independence and Security Act of 2007 (EISA) through energy-use breakdown estimates (Fisher, 2014). Legal compliance to EISA section 432 (EISA, 2007) requires applicable federal facilities to undergo energy audits every four years. EISA compliance can be met by the American Society of Heating, Refrigeration and Air-conditioning (ASHRAE) commercial building energy audit levels one to three (ASHRAE, 2011). To do this, the models must produce estimates of the energy and water savings opportunities for each building. Unfortunately, an audit of SNL's fleet in 2016 found only 52% of the models met ASHRAE Guideline 14 calibration requirements. This result warned that it was unlikely that energy savings opportunities were accurate even though calibration status is not an exact indicator. This led to planning for maintaining SNL's fleet of models through a systematic process. The need for methods to reduce workloads for such a large set of models suggested automated calibration techniques might be helpful (Chaudhary et. al., 2016). This in turn led to collaboration for auto-calibrating the fleet of models. Manual intervention was also planned through quality checks of the model versus energy audit reports (Villa et. al., 2018). This paper presents the design of a quality check and automatic calibration procedure on our BEM fleet that is planned to be systematically applied to models to accompany conventional building energy audits. It then walks through the results for the first five buildings involving both quality checks and auto-calibration.

METHODS

The preparation of models for auto-calibration is challenging. The DOE2.2 BEMs had many Building Design Language (BDL) expressions and global parameters for ECMs but these were not designed to touch every part of the model needed for calibration purposes. This was overcome by creation of software that automatically inserts two types of parameters: multipliers and base-load offset parameters (Villa et. al., 2018). Generalized BDL expressions were derived that produce no change to any original BDL expression if the parameter has a default value. Multipliers have a default numerical value of one and output the product of the multiplier and any existing BDL expression. Base-load offset parameters are applied to schedules and have a default value of zero. At negative one, the baseload offset stretches the schedule to zero baseload. At one, the baseload offset compresses the schedule to baseload equal to peak load as seen in **Error! Reference source not found.**. The functional relationship to transform any function this way is given in equations (1) and (2).

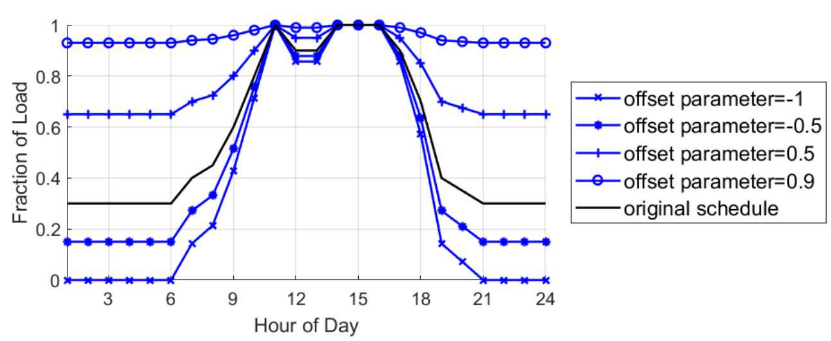


Figure 1. Baseload offset parameter effects on an hourly load schedule for one day as defined by equation (1).

$$f_{new}(t) = \begin{cases} (1 - p_{off})f(t) + f_{max}p_{off} & 1 \geq p_{off} \geq 0 \\ -p_{off}f_{new_{-1}}(t) + (p_{off} + 1)f(t) & -1 \leq p_{off} < 0 \end{cases} \quad (1)$$

$$f_{new_{-1}}(t) = \frac{f_{max}}{f_{max} - f_{min}} f(t) - \frac{f_{max} f_{min}}{f_{max} - f_{min}} \tag{2}$$

Here, p_{off} is the base-load offset parameter, $f_{max} = \max(f(t))$, $f_{min} = \min(f(t))$. It is assumed for this application that $f(t)$ is an hourly function of up to 8,760 values but any function that is bounded over a given interval can work.

Sixteen multipliers and five base-load fraction parameters were created that alter building envelope, HVAC cooling efficiency, equipment schedules, exhaust schedules, fan schedules, heating efficiency, cooling efficiency, heat rejection efficiency, infiltration, lighting schedules, occupancy schedules, outdoor air flow, plug loads schedule, pumping efficiency, and non-electrical source load schedules. The underlying software applies the parameters across a broad range of systems and BDL command types. Over fifty-five BDL keywords per building are referenced by a total of 255 tunable calibration parameters (13 for Building 1, 56 for Building 2, 49 for Building 3, 70 for Building 4, and 67 for Building 5). A subset of these parameters is provided as supplemental information. These typically included 21 calibration parameters that were previously defined for use by the community (Villa et. al., 2018). The changes to BEM from insertion of these parameters are extensive with two examples shown in Figure 2. The lower example illustrates that existing expressions are preserved. There were approximately 49 previously defined parameters that were leveraged for site-wide energy assessments when available (number of parameters varied by building). Even though it was intended for these changes to the model to not alter its output, some changes in model energy consumption were observed after changes were made. Investigation concerning why this is the case is still underway but BDL's handling of default and missing values is probably the issue.

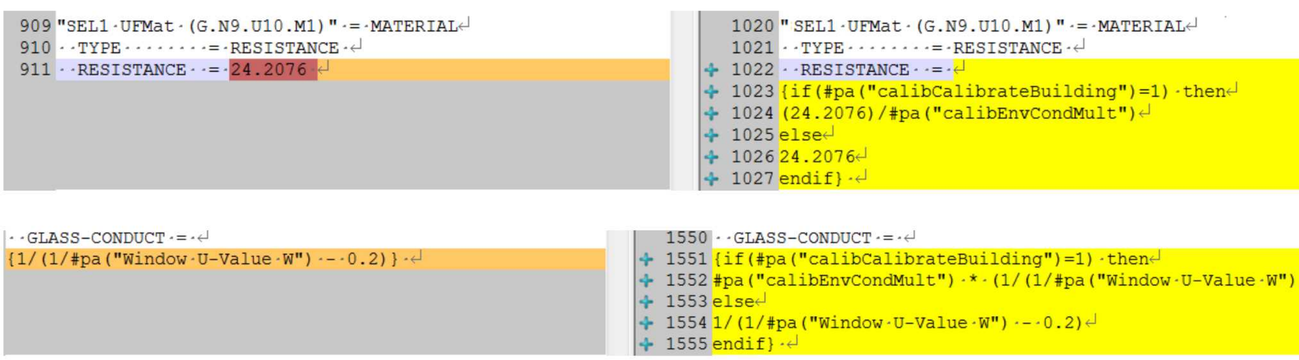
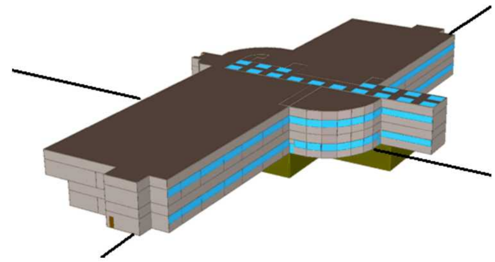
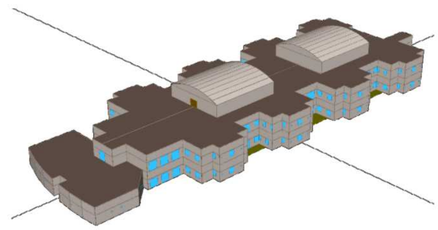
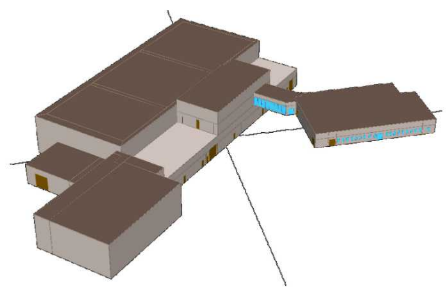
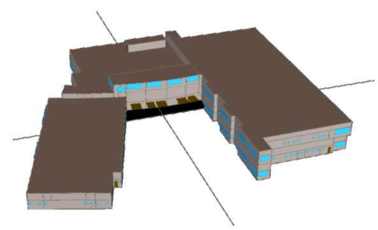
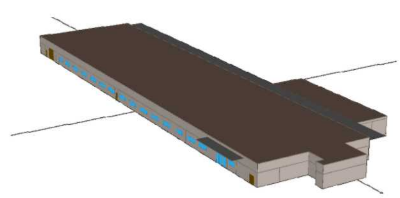


Figure 2 A BDL expression before and after insertion of calibration parameters shows how calibration is accommodated or else preserves the original parameter value.

Quality checks (QC) were confined to verification that building-specific details from existing energy audits were consistent. The reviewer was required to verify that a BEM could run before and after changes were made. An average of 6 hours per building was spent generating a spreadsheet that lists where the model was consistent, areas that were corrected, and issues that were not correctable (and why) in the time frame available. The BEM model was also checked for errors in modeling methodology with investigation of all output warning messages from DOE2.2. Finally, a list of information in the energy audit that could not be usefully applied to the BEM was required. The reviewer finished the quality check by assigning a grade to the BEM: A = ready for calibration, B = ready for calibration but with known issues, C = known issues are serious and the reviewer is uncertain whether to calibrate, D = calibrating is not recommended but known corrective action may correct issues, F = fundamental flaws exist or DOE2.2 is incapable of simulating the building accurately.

Seventeen buildings were chosen to undergo auto-calibration in 2018 of which five were finished in time for this paper. The five buildings are listed in Table 1 which gives the general attributes, calibration status, and QC grade. The buildings are highly complex, have multiple uses that vary sporadically, and many instances of 24-7 operations.

Table 1 Building Attributes and Calibration Status 2014

Building	Description	Model Picture from eQUEST®
Building 1 Albuquerque New Mexico Built 1987	• 3 level 72,200ft^2 (6,710m^2) Light Lab with pre-cast concrete panels with exterior metal panels • 2 24-7 exhaust systems. • Mixed single duct and dual duct • 5.42 GWh (18,490 MBTU) electricity consumption 2017 • Calibrated om 2014 to NMBE -2.92% CV(RSME) 5.41%. No QC Grade	
Building 2 Albuquerque New Mexico Built 1995	• 3 Level 98,200ft^2 (9,120m^2) Light Lab with concrete masonry unit construction • 2 24-7 exhaust systems • Compressed air services • 2.26 GWh (7,710 MBTU) electricity consumption 2017 • 2,210 MCF (62,580m^3) natural gas used 2017 • Out of compliance for calibration in 2014. NMBE 5.50% CV(RSME) 6.40% QC Grade A	
Building 3 Albuquerque New Mexico Built 1984	• 2 Level 76,100ft^2 (7,070m^2) Highbay area with office space attached by a skybridge. Mostly precast with Double tee structural walls • Compressed air services • 1.57 GWh (5,360 MBTU) electricity consumption 2017 • 4,047 MCF (114,600m^3) natural gas used in 2017 • Out of compliance for calibration in 2014. NMBE 12.05% CV(RSME) 13.00% QC Grade A	
Building 4 Livermore California Built 2003	• 2 Level 71,500ft^2 (6,643m^2) steel frame office building • Administrative offices and large conference room center. • Small café and dining area • 3.91 GWh (13,300 MBTU) electrical consumption 2017 • Not calibrated in 2014. QC Grade B	
Building 5 Livermore California Built 1958	• 1 Level 32,600ft^2 (3030m^2) concrete office building • 4-ply built up cool roof • 1.82 GWh (6,210 MBTU) electricity consumption 2017 • 6,050 MCF (171,300m^3) natural gas used in 2017 • Not calibrated in 2014. QC Grade C	

The calibration methodology used in this study is the Autotune technology (New et. al., 2012). The core Autotune capabilities were developed at Oak Ridge National Laboratory over the course of 3 years by leveraging 8 high performance computers (including two of the world's #1 fastest supercomputers), 218 Linux machines, and development of a software system for running a suite of machine learning algorithms (MLSuite) on these resources in parallel (Edwards, 2013a) composed of proprietary, open source, and computational complexity improvements (Edwards, 2013b) to artificial intelligence (AI) algorithms. A set of over 8 million simulations totaling over 300 terabytes (TB) was mined with different algorithms, techniques, meta-parameters, calibration metrics, and combinations of AI methods via ensemble learning. Over 300,000 AI algorithmic instances with a single parallel run of over 130,000 AI instances were utilized that included the following classes of algorithms: linearly and non-linear regression, feed forward and recurrent neural networks, C- and K-means clustering with local models, support vector machines, Gaussian mixture models, self-organizing maps, regression trees, time modeling, and genetic algorithms. The best-performing algorithm on a benchmark dataset of 20,000 buildings was a custom modification to the NSGA-II algorithm, which resulted in an average hourly CV(RMSE) below 4% (Garrett et. al. 2013, Garrett and New 2015, Chaudhary et. al. 2016). More importantly, this algorithm used a new ANSI/RESNET standard (ANSI 1201-2016) to quantify the recovery of the actual input parameters of the building between 15% and 32%, with better performance achieved with more channels of higher-resolution energy and non-energy performance data (New et. al., 2018). The core Autotune algorithm was further extended to DOE-2.2 simulations required for this study. This included modification of BDL variables and scalable parsing of DOE-2.2 output reports to enable improved calibration.

While not often reported in the literature, there are several practical considerations that many calibration studies face including BEM modifications, sensed data cleanup, selection of tunable parameters, properties of those parameters (e.g. min, max, distribution, grouping, mathematical constraints), and re-calibration via modifications of these when improved comparison data is provided from a calibration. In this study, the original building energy models were specified for a time period from March 27 – December 31, 2012 and January 1, 2012 – March 6, 2013. For this study, we modified the time period to January 1 – December 31, 2017 (the year is not important but the time series reported needs to align with the sensed data). There were several sensed data cleanups, which is an ongoing challenge for many organizations with respect to centralizing and providing quality assurance/control of metered data (that may cover multiple buildings or overlap measurement boundaries with other analysis). While it is standard practice to calibrate on the last 12 months of data, to minimize the odds of a non-routine adjustment, we find comparison of those 12 months to previous years of data to be a useful exercise. Building 2 experienced a faulty natural gas meter in June that was detected as anomalous compared to the previous three years so the usage was doubled. Building 3's electrical use was increased 67% due to an anomalous change in operations that is unlikely to repeat in the future. Building 4's energy use for August – December was averaged from previous years due to similar operational concerns. The authors find that most organizations and individuals end up re-evaluating the tunable parameters and properties after calibration once the modeled and measured data are compared together. Most of the reasoning and selection for the parameter properties used in this study are discussed previously (Villa et. al., 2018). We also find providing clear guidance on what is expected in a calibration report is useful. For this study, the final report for each building included an interactive report with the following information:

- Documentation of the quality check process with comparison to walkthrough audit data
- Prominent display of the final NMBE and CV(RSME) values achieved
- The final building energy model
- The building energy model before calibration
- Full details in result files for the final calibrated model
- Graph providing monthly building energy performance data of electricity/gas (if provided) versus the final calibrated building energy model performance
- Spreadsheet providing all the parameter values determined by the calibration algorithm
- The Actual Meteorological Year (AMY) weather file corresponding to the time period in which data was collected
- The measured calibration data used
- Meta-information regarding the computer used, dates of run, individual who performed the analysis, contact

information, and additional important notes
- Graph and data showing yearly end-use break-down by Heating, HVAC cooling equipment, HVAC Fans, interior lights, pumps, plug loads, interior lighting, and other loads
- Short notes concerning whether the end-uses are close to typical end-uses for the building type being evaluated

Archiving these results provides a permanent record of the analysis that allows direct application to the EISA energy audits and creation of a permanent link that allows replication or further investigation as needed.

RESULTS

For Building 1, the authors began with the original BEM model and a manually-calibrated model. Automatic calibration was applied to the manually-calibrated model to determine if it could improve beyond the manual calibration and to achieve the most accurate model for assessing energy savings opportunities. However, this calibration-on-top-of-calibration can lead to further differentiation of model inputs from walkthrough audit data. In addition to addressing this concern, the authors sought to determine if automatic calibration of the original model could have saved the cost and expense of the manual calibration, especially in regard to matching measured energy use. Building 1 was calibrated using hourly data, but accuracy metrics are also shown for daily and monthly in Table 2 to inform how well the method generalizes across different temporal resolutions.

Formal interviews by the authors with individuals holding the job title of "energy engineer" that typically perform calibration services for Energy Service Companies (ESCOs) have identified an average of approximately 24 hours to manually calibrate a building of this size at an average fully-burdened rate of $130/hour. Using this assumed hourly rate, we show improved calibration performance and a savings of approximately $1,000 (29%) for this building and 12-20 hours in turn-around time. This value grows non-linearly with the increasing amount of sensed data, complexity of operations, number of calibration parameters, and the size of the building portfolio being calibrated.

Table 2. Building 1's monthly, daily, and hourly accuracy of the original model, auto-calibration, manual-calibration (from original), and auto-calibration (from manually-calibrated) shows generally better accuracy than manual calibration, minor cost savings, and increased scalability to cost-effectively address larger portfolios of buildings.

		Original Model	Autotune (from original)	Manual Calibration	Autotune (from manual)
Monthly utility data	CV(RMSE)	8.37%	5.22%	5.23%	5.20%
	NMBE	2.66%	0.16%	-1.42%	0.66%
Daily utility data	CV(RMSE)	12.41%	9.11%	8.26%	7.53%
	NMBE	2.66%	0.16%	-1.42%	-0.26%
Hourly utility data	CV(RMSE)	19.50%	10.9%	11.54%	9.70%
	NMBE	2.66%	0.16%	-1.42%	-0.26%
Cost			$2.5k (15 hours, compute)	27 person-hours ($3.5k at $130/hr)	$2.5k (7 hours, compute)

In performing the calibration for all 5 buildings, there were several real-world considerations that were noted as part of the analysis. First, most of the tunable parameters selected only affected electrical energy use. While some natural gas parameters were added, this was done after-the-fact and had little impact on natural gas energy use. When calibrating to items beyond whole-building electrical (e.g. natural gas, water), calibration benefits from significant forethought in the uncertainty of the major variables that affect those points of measure. With regards to natural gas, we noted several recommendations including the following:

- Buildings 2 and 3 natural gas base loads needed for summer and shoulder seasons

- Building 2 electricity values were unusual for February, July, and September compared to previous years,
- Building 3 likewise deviated in February and September compared to previous years,
- Building 4 had identical values in July, August, and September compared to the previous year and could be a potential copy/paste error,
- Building 5 had 30x greater energy consumption for natural gas than the calibrated model with a 77% weather-independent base load and 23% weather-dependent (assumed to be space heating), and
- Building 5 results were within 1% on an annual basis but off by as much as 30% on a monthly basis due to 6–27% lower than measured for January-August but 27–33% higher than September – December with measured energy use falling sharply between July and September. Since no building or operational change was noted in the supplied audit, it was conjectured that a model calibrated on only the last half of the year may be more valuable going forward.

	Original				Tuned			
	Electricity		Gas		Electricity		Gas	
Building	CV(RMSE)	NMBE	CV(RMSE)	NMBE	CV(RMSE)	NMBE	CV(RMSE)	NMBE
1	8.4%	2.7%	--	--	5.2%	0.7%	--	--
2	125.9%	125.4%	81.5%	54.3%	17.3%	13.5%	37.8%	13.8%
3	13.3%	-7.9%	47.8%	-42.5%	9.5%	-0.26%	13.9%	-1.4%
4	5.6%	2.3%	--	--	4.8%	0.2%	--	--
5	29.7%	-28.7%	97.3%	-96.2%	6.5%	-1.8%	97.8%	-96.6%

ASHRAE Guideline 14 NOT G14

Figure 3. Monthly BEM accuracy pre- and post-calibration. While ASHRAE Guideline 14 is almost exclusively applied to whole-building electrical use, future versions are considering submetering, higher-resolution sampling, and the (generally) more difficult challenge of matching natural gas or water use.

To get a sense of how much change was required to achieve calibration, the percent change across the allowed minimum to maximum ranges was calculated for each parameter for Buildings 2 through 5. This resulted in 236 data points concerning how much the auto-calibration procedure varied parameters (Figure 4). The resulting distribution has an average of 1.56% which we assume is converging to zero and a sample standard deviation of 30.07%.

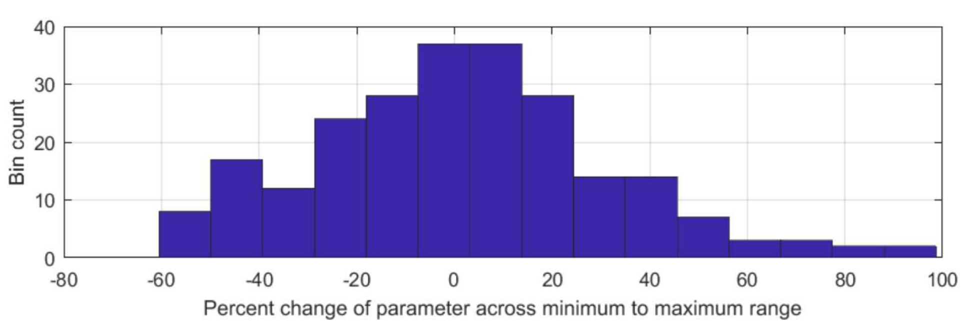


Figure 4. Auto-calibration parameter percent change

Such a high standard deviation is well beyond the desirable range of adjustment based on the authors' judgment. We hypothesize that it is indicative that the models are not sufficiently configured to represent the real building well. It is much more desirable for auto-calibration to tune a model that represents a real building accurately but for which unknown efficiencies and variations in schedules require some adjustments. There are many parameters, such as the shapes of schedules or thermal zone configurations, which cannot be altered by the auto-calibration and are too complex to be adjusted by the optimization schemes given computational limitations. The authors had hoped for auto-calibration to achieve system identification of a core set of parameters such as efficiencies, changes to envelope, and changes to base and peak loads. Instead, we think that the models are being drastically changed by the optimization scheme to fit models that need to be configured more accurately before calibration. We think that this can be resolved by tighter connection to living data sources in the building.

CONCLUSION

Five BEMs have been successfully auto-calibrated and twelve more are in process. For our case, the auto-calibration process has provided much needed deliverables for EISA 2007 compliance at economically competitive rates. Though reduced cost has been demonstrated, the reduced hours of labor required to calibrate models is of greater importance for SNL's needs. Initiating the auto-calibration process has also elucidated the need for improvements to our data collections processes and methods for maintaining large fleets of BEMs. The quality checking procedure was found to be essential and even revealed misinformation in energy audit reports that was able to be corrected, making it a valuable exercise beyond the benefits for our efforts. Though two of the models did not achieve ASHRAE Guideline 14 compliance, all the models were drastically improved. For the failed cases, data and modeling accuracy issues are more likely at fault than any shortcomings of our auto-calibration procedure.

This work has revealed the need for refinement of many of the energy tracking processes at large institutions across our nation. For auto-calibration to be effective, BEM fleets need to be efficiently connected to building automation systems with automated data to model comparisons. Auto-calibration will then have a richer dataset and will better serve its designed purpose of tuning a model for immediate identification of parameters. Because of the lack of such connections, we think that this work has involved fitting poorly configured models that actually need addition of missing systems, reconfiguration of existing systems, and corrections to schedule shapes. The drastic changes to parameters needed (Figure 4) for Buildings 2 through 5 give evidence that this was the mode of operation for this work so far. We plan to correct this and to implement the measures already mentioned. As these refinements are made, we expect to be able to open our BEM fleet to energy analytics applications that assist in identification of sudden unexpected changes in operations. To do this, auto-calibration will have to be done on a much more frequent basis than every four years. We think that we need to comprehensively classify every parameter in every model into four categories: 1) no changes needed, 2) discoverable by available data, 3) undiscoverable by available data, and 4) tuned by auto-calibration. The third category needs to be kept to a minimal set and can only be addressed by uncertainty analysis. Such classification may serve as a basis to analytically estimate whether a model is accurate. Significant work is needed to be able to quickly classify BEMs into these categories. Regardless, our current efforts have shown methods that reduce resources required to maintain large fleets of BEMs.

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