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Cost-effective Measurement and Verification Method for Determining Energy Savings under Uncertainty

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ABSTRACT

For measurement and verification (M&V) of energy savings in buildings, we propose an approach based on Gaussian Process (GP) modeling that can represent nonlinear energy behavior, multivariable interactions, and time correlations while quantifying uncertainty associated with predictions. We applied GP modeling to determine energy savings from BuildingIQ's energy management system deployed at the Advanced Photon Source Office building at Argonne. The case study demonstrates the potential strengths of GP models for M&V and explores the importance of dataset characteristics and explanatory variables for the reliability of analysis results. The case study illustrates the capability of GP modeling to predict hourly dynamic behavior, exploiting the possibility to reduce uncertainty in energy-use predictions using measured data with finer time resolutions. The proposed M&V approach is amendable to automation in energy management systems and continuous monitoring of energy performance.

INTRODUCTION

Enhancing the energy efficiency of existing buildings has been one of the major requirements for meeting America's national-level energy reduction targets. The American Recovery and Reinvestment Act (ARRA) funded about $16 billion for state and local government energy efficiency programs over 3-4 years (Schiller et al., 2011). Also, about 35 states implemented ratepayer-funded energy efficiency programs with a total budget of $3.1 billion in 2008 (Barbose et al., 2009). These energy efficiency programs have adopted the Energy Efficiency Resource Standard, which requires utilities to achieve a certain energy-savings target by improving energy efficiency of buildings, distribution systems, and power generation systems. In most states, utilities often spend a large portion of their program costs for enhancing the energy efficiency of buildings; indeed, 50% of the ARRA State Energy Program fund was allocated for building retrofits in 2009 (Goldman et al., 2011). The Federal Energy Management

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Program (FEMP) in the Department of Energy also allocated $2 billion in energy-savings performance contracts (ESPCs) and utility energy-savings contracts to help federal agencies accomplish energy savings in their facility operation (ESPC, 2012). These contracts are enacted with energy service companies (ESCOs), which are expected to have annual revenues of $7.1−7.3 billion in 2011 (Satchwell et al., 2010). Beyond the retrofit efforts at the government level, private building owners invest in energy retrofits to reduce utility bills and increase long-term real estate value.

For regulated energy efficiency programs and ESCOs, measurement and verification (M&V) of energy savings is a crucial business requirement. As part of performance-based contracts, ESCOs perform the M&V process of estimating energy savings achieved during the contract period, typically following the International Performance Measurement and Verification Protocol (IPMVP, 2010). Under the IPMVP approach, ASHRAE Guideline 14 provides technical details of modeling energy use, handling uncertainty in analysis, and validating analysis results, specifically for ESCO performance-based contracts (ASHRAE, 2002). In alignment with IPMVP and ASHRAE Guideline 14, FEMP also developed M&V guidelines that ESCOs should comply with in federal energy-savings performance contracts (FEMP, 2008). Furthermore, ARRA provides monitoring and reporting requirements to assist in evaluating the energy savings achieved from implemented actions (Recovery Act, 2012). The technical guidance in the requirements is consistent with the M&V options specified in the IPMVP.

For determining energy savings from energy efficiency measures (EEMs), IPMVP and ASHRAE Guideline 14 provide multiple calculation methods that estimate energy savings by using either building simulation models or measurement data (IPMVP, 2010; ASHRAE, 2002). For the method based on measurement data, one develops change-point linear regression models to capture nonlinear energy behavior for different regimes (e.g., heating/cooling, weekday/weekend) during the pre-retrofit period, typically as a function of outdoor air temperature. With the pre-retrofit models developed, one predicts baseline energy use corresponding to the post-retrofit-period conditions. This step is required to calculate energy savings solely due to EEMs and excluding the effects of other factors such as weather conditions and changes in building usage patterns. Last, one obtains energy-savings estimates by subtracting measured energy use during the post-retrofit period from that predicted by the pre-retrofit regression models.

For compliance, a maximum allowable uncertainty (X% uncertainty at Y% level of confidence) in the calculated energy savings must be specified for the selected M&V performance path. The guideline further stipulates that the maximum allowable uncertainty be set at a minimum of 50% of the calculated energy-saving estimate at 68% confidence. The guideline allows for any applicable uncertainty analysis method published in statistical textbooks to be used. It also provides a few simplified methods for the uncertainty quantification. Equation 1 is one example, derived from linear regression models with additive errors constant over the whole regime (Reddy and Claridge, 2000). In the equation, E_{saving} refers to the energy-savings estimate aggregated over *m* observations during the post-retrofit periods, ΔE_{saving} is the prediction uncertainty in estimated annual savings, and *n* is the number of observations during the pre-retrofit period. CVRMSE is the coefficient of variation of the root mean square error between predicted and measured baseline energy use over *n* observations; *t* is a t-statistic for the expected confidence level, and *F* refers to the ratio of the energy-savings estimate to the pre-retrofit energy use.

$$\frac{\Delta E_{saving}}{E_{saving}} = t \cdot \frac{1.26 \times \mathrm{CVRMSE} \times \sqrt{\left(1+\frac{2}{n}\right) \times \frac{1}{m}}}{F} \quad (1)$$

Equation 1 and statistical modeling techniques commonly used for M&V have two limitations. First, they do not capture the multivariate interactions of explanatory variables on energy use. Consequently, complex energy behaviors may not be adequately predicted by the models used for M&V. Second, simplified uncertainty estimation techniques do not provide information on the effect of data availability on prediction uncertainty. The capability to determine point-by-point uncertainties holds promise to reduce the amount and cost of data collected.

Researchers have developed new inverse models for modeling baseline energy use on the basis of measurement data. ASHRAE held the "Greate Energy Predictor Shootout" in which contestants applied their inverse modeling algorithms to train hourly energy models (Kreider and Haberl, 1994). Most of the highly ranked algorithms are based on neural network models, and the winner's algorithm is based on Bayesian modeling using neural networks. In this paper, we propose a new standards-compliant approach based on Gaussian Process (GP) modeling that can represent nonlinear energy behavior, multivariable interactions, and time correlations while quantifying uncertainty associated with predictions. The proposed M&V approach uses measured data and is amenable to automation in energy management systems (EMSs) and for continuous monitoring of energy performance. A case study demonstrates the application and strengths of GP models for M&V.

GAUSSIAN PROCESS MODELING

For developing statistical models, we propose GP modeling as a new method that can reliably predict energy savings while quantifying uncertainty associated with predictions. The technique is data-based, follows a Bayesian setting, and is a generalization of nonlinear multivariable regression. Unlike standard regression models that pre-determine relationships between explanatory and dependent variables, GP models specify the structure of the covariance matrix of explanatory variables. This feature enables GP models to capture complex, nonlinear trends that result from multivariable interactions. Furthermore, since GP models are formulated as probabilistic models under a Bayesian setting, they can naturally quantify uncertainty in their predictions. The capability to quantify confidence levels associated with different energy use regimes will be especially useful in the many M&V cases in which only limited, sparse data are available. For a detailed description of the GP modeling method, mathematical formulations, strengths, and limitations, the reader is referred to Heo and Zavala (2012).

A GP model regresses a set of explanatory variables $\mathbf{x}$ to an output variable $\mathbf{y}$ as specified by a mean function and a covariance function. A mean function is a matrix of mean output values for the given set of input values, and is typically assumed to be zero. A covariance function is a matrix, each element of which indicates proximity between two input vectors with respect to their outputs. For two input vectors $\mathbf{x}(i), \mathbf{x}(j)$, the covariance matrix $\mathbf{V}(\mathbf{X}, \mathbf{X}, \eta)$ is defined by Equation 2, in which $i, j = 1, \dots, n$ and $\|\cdot\|$ is the Euclidean norm. $\eta = [\eta_0, \eta_1, \eta_2]^T$ are covariance function hyperparameters that control the model's predictive power. η_0 accounts for measurement errors in the output, η_1 controls the precision of the GP model, and η_2 controls correlation strength in each input parameter. The formulation of the covariance function accounts for modeling uncertainty and uncertainty in measured energy use while assuming that explanatory variable values are deterministic. The GP model is trained through the log likelihood function that updates the hyperparameter values that maximize the data likelihood. Equation 3 defines the log likelihood function: $\mathbf{m}(\mathbf{X})$ is the mean function for input vector set $\mathbf{X}$ in the training dataset, and $\det(\mathbf{V}(\mathbf{X}, \mathbf{X}, \eta))$ refers to the determinant of the covariance matrix.

$$\mathbf{V}(\mathbf{X}, \mathbf{X}, \eta)[i, j] = \eta_0 + \eta_1 \cdot \exp(-\frac{1}{\eta_2} \|\mathbf{x}(j) - \mathbf{x}(i)\|^2) \tag{2}$$

$$\log p(y|\eta) = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\left(\mathbf{y} - \mathbf{m}(\mathbf{X})\right)^T \mathbf{V}^{-1}(\mathbf{X}, \mathbf{X}, \eta)\left(\mathbf{y} - \mathbf{m}(\mathbf{X})\right) - \frac{n}{2}\log\det(\mathbf{V}(\mathbf{X}, \mathbf{X}, \eta)) \tag{3}$$

After training the model, we obtain the optimal hyperparameter values η^* that determine mean function values μ_{test} and covariance matrix $\mathbf{V}_{test}$ for new test input matrix $\mathbf{X}_{test}$. The mean and covariance matrixes of the model predictions are defined in Equations 4 and 5, respectively.

$$\mu_{test} = \mathbf{V}(\mathbf{X}_{test}, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X}, \mathbf{X}, \eta^*)\mathbf{y} \tag{4}$$

$$\mathbf{V}_{test} = \mathbf{V}(\mathbf{X}_{test}, \mathbf{X}_{test}, \eta^*) - \mathbf{V}(\mathbf{X}_{test}, \mathbf{X}, \eta^*)\mathbf{V}^{-1}(\mathbf{X}, \mathbf{X}, \eta^*)\mathbf{V}(\mathbf{X}, \mathbf{X}_{test}, \eta^*) \tag{5}$$

CASE STUDY

This section demonstrates the strengths of GP modeling for M&V applications through a case study. We implemented an EMS in the Advanced Photon Source (APS) office building at Argonne National Laboratory. The building is a five-story, 190,000 square foot building that consists of cellular offices, seminar rooms, and laboratories. The building has two air-handling units (AHUs) that provide fresh air and supply air cooled by district chillers serving the entire APS site. The building has reheat coils in terminal units that reheat cooled supply air to meet heating demands in individual spaces. The EMS implemented in the building is the BuildingIQ system, which optimizes supply-air temperature and static pressure setpoints to reduce energy use while maintaining occupants' thermal comfort (Zavala et al., 2011). The system includes a black-box model that captures the effects of weather conditions, control variables of interest, and AHU energy use (chilled-water energy use, in this case) on aggregate-level zone temperature. Table 1 summarizes the numbers of hourly data points collected during the pre-retrofit period (without the EMS operating) and during the post-retrofit period (with the EMS operating). The data set contains a larger number of post-retrofit data points covering a wider span of weather variations, including extremely cold weather conditions, compared to a smaller number of pre-retrofit data points. This situation is common in retrofit projects, in which the collected data are often sparse and limited. Given the limited dataset, quantifying uncertainty associated with predictions is crucial to reliably determining energy savings.

Table 1. Summary of Collected Data

	Number of Hourly Datasets	Ambient Temperature Range	Data Collection Period*
Pre-retrofit Period	536	9.0 degC – 37.5 degC	May-August 2012
Post-retrofit Period	3136	-22.8 degC – 35.0 degC	February-October 2012

*The BuildingIQ system was operated on intermittent days in May-August to collect pre-retrofit data.

Developing GP Models for Predicting Hourly Energy Use

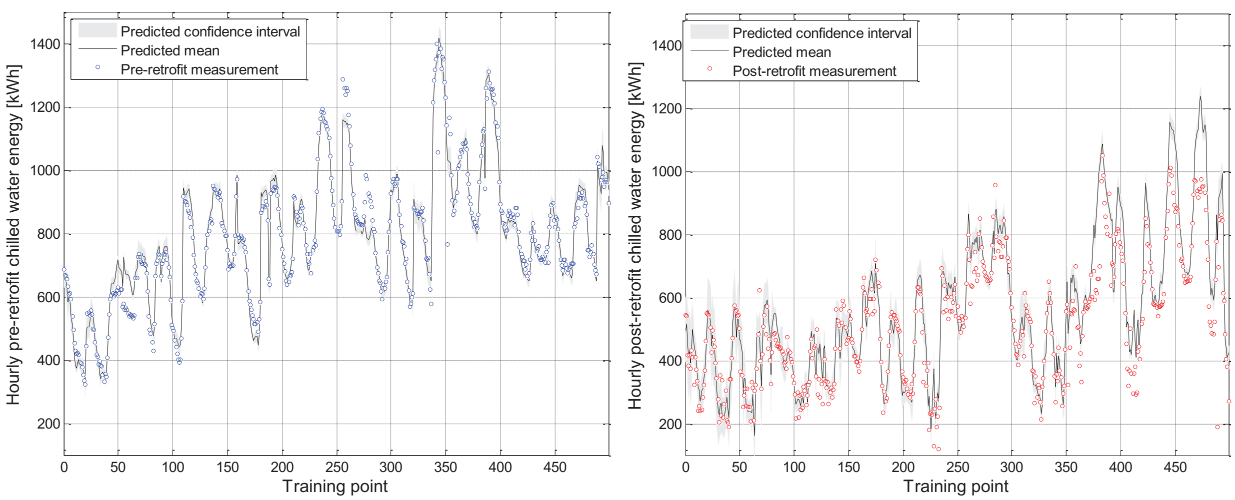
Heo and Zavala (2012) showed that GP models can be used to predict hourly energy use in buildings and that finer-resolution data could help reduce uncertainties in the analysis. With this approach, we are able to fully exploit diurnal variations in weather and building conditions, increasing the available measured data by more than an order of magnitude during a set sampling period. Developing GP models for finer-resolution data requires special attention to designing a set of explanatory variables that enable the GP model to capture complex energy trends.

For predicting hourly chilled-water energy use, we used three-step measured values (at times t, t -1, and t -2) for each explanatory variable to capture delay in the effect of the explanatory variables on energy use at time t due to thermal lag. Table 2 summarizes the reliability of test predictions with different sets of explanatory variables. The predictive power of the GP model is evaluated by two statistical metrics: (1) SSE, i.e., the total sum-of-squares error in the expected energy use prediction compared to measured energy, and (2) C.I., i.e., 95% confidence intervals of model predictions. Case 1 represents typical M&V practices that use ambient temperature (T_{amb}) as the only explanatory variable. By adding ambient relative humidity (RH_{amb}), Case 2 significantly reduced SSE and C.I., whereas incorporating solar radiation (SR) in Case 3 did not enhance the model's predictive power much. Case 4 introduces the CO_2 concentration of return air (CO_2^{return}) as a surrogate parameter to capture occupancy variations. Including this variable in the model derivation noticeably reduced SSE. As seen in Cases 4 and 7, adding outdoor air flow ($F_{outdoor}$) or the economizer position ($S_{economizer}$) had a small overall effect on the model's predictive power. Case 9, which uses the three variables T_{amb}, RH_{amb}, and CO_2^{return}, yields the model with the lowest SSE and C.I. When additional variables beyond those three were incorporated (Cases 10 and 11), SSE and C.I. increased because the dataset may not fully explain interactions between the explanatory variables. Hence, for this evaluation, we used ambient temperature, ambient relative humidity, and CO_2 concentration of return air as explanatory variables for developing pre-retrofit and post-retrofit models. These analysis results suggest that M&V does not necessarily require deep monitoring of building operation but needs only metered energy-use data and a realistic estimate of occupancy patterns.

Table 2. Effect of Different Sets of Measured Explanatory Variables on Model Predictions

	Explanatory Variable (at times *t*, *t*-1, and *t*-2)	Pre-retrofit Model SSE	Pre-retrofit Model C.I.	Post-retrofit Model SSE	Post-retrofit Model C.I.
1	T_{amb}	3.71×10^6	3.85×10^3	4.79×10^7	1.39×10^4
2	T_{amb} + RH_{amb}	9.55×10^5	2.08×10^3	3.29×10^7	1.16×10^4
3	T_{amb} + SR	3.64×10^6	3.84×10^3	4.61×10^7	1.36×10^4
4	T_{amb} + CO_2^{return}	3.32×10^6	3.70×10^3	4.21×10^7	1.30×10^4
5	T_{amb} + $F_{outdoor}$	2.34×10^6	3.15×10^3	4.69×10^7	1.38×10^4
6	T_{amb} + RH_{amb} + SR	1.79×10^6	2.80×10^3	3.30×10^7	1.16×10^4
7	T_{amb} + CO_2^{return} + $F_{outdoor}$	2.16×10^6	3.06×10^3	4.30×10^7	1.32×10^4
8	T_{amb} + $F_{outdoor}$ + $S_{economizer}$	2.34×10^6	3.15×10^3	4.68×10^7	1.37×10^4
9	$\mathbf{T_{amb} + RH_{amb} + CO_2^{return}}$	$\mathbf{7.84\times10^5}$	$\mathbf{1.94\times10^3}$	$\mathbf{2.69\times10^7}$	$\mathbf{1.06\times10^4}$
10	T_{amb} + RH_{amb} + CO_2^{return} + $F_{outdoor}$	1.15×10^6	2.25×10^3	3.66×10^7	1.22×10^4
11	T_{amb} + RH_{amb} + SR + CO_2^{return}	1.78×10^6	2.79×10^3	2.85×10^7	1.09×10^4

Figure 1 compares measured energy use with hourly predictions of the pre-retrofit and the post-retrofit models using the Case 9 explanatory-variable set. These results indicate that the GP models with the three Case-9 variables capture hourly dynamic energy trends. Although discrepancies between predicted means and measurements are observed, most of the measured data lie within the C.I. We note that discrepancies for the post-retrofit predictions are noticeably larger than those for the pre-retrofit predictions: this trend could be attributed to the dynamic, predictive HVAC control of the EMS that may not be fully explained by the selected variables.

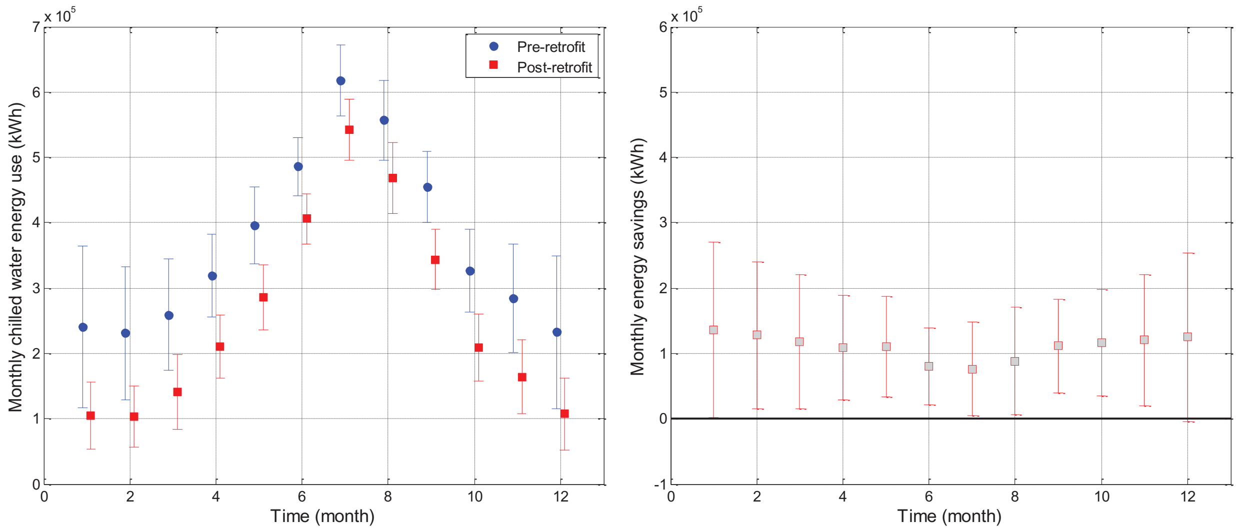


(a) (b)

Figure 1 (a) Hourly pre-retrofit chilled-water energy use predictions (black line) compared with pre-retrofit measured energy use (blue dots) and (b) hourly post-retrofit chilled-water energy use predictions (black line) compared with post-retrofit measured energy use (red dots)

Estimating Energy Savings

In practice, M&V projects calculate energy savings by developing pre-retrofit energy models and subtracting measured post-retrofit energy-use values from those predicted using the pre-retrofit energy model. In our case study, we modeled both hourly pre-retrofit and post-retrofit energy using measured data for standard yearly weather and occupancy conditions. We used Typical Meteorological Year (TMY) weather data and generated stochastic CO_2 profiles by randomly selecting an hourly CO_2 concentration from the probabilistic distributions derived on the basis of collected CO_2 concentration per time of day for weekdays and weekends. By aggregating probabilistic hourly predictions, we obtain monthly pre-retrofit and post-retrofit energy use. The mean of the monthly energy use is the summation of all hourly energy use predictions corresponding to each month, and the variance is the summation of the covariance matrix corresponding to each month. Figure 2 shows monthly pre-retrofit and post-retrofit chilled-water energy use (left side) and energy-savings predictions (right side). Solid points refer to mean values, and whiskers refer to associated 95% C.I. The hourly GP model was able to predict pre-retrofit energy use during the winter season by fully exploiting hourly data. However, owing to the lack of data, the pre-retrofit predictions corresponding to this period have much wider C.I. compared to the rest of the year. Annual energy-savings estimates are derived following the same time-aggregation approach; the mean annual energy-savings estimate is 1.32×10^6 kWh (30% energy savings compared to the pre-retrofit chilled-water energy use), with C.I. ranging between 3.33×10^5 and 2.31×10^6 kWh.



(a) (b)

Figure 2 (a) Aggregated monthly energy use predictions, pre-retrofit (blue circles) and post-retrofit (red squares), and (b) monthly energy savings

The GP regression method directly computes the energy-savings uncertainty at different levels of confidence. Table 3 provides prediction uncertainties from our case study for comparison to the ASHRAE minimum compliance criteria of 50% uncertainty at 68% confidence. Overall, for monthly energy-savings estimates, prediction uncertainty at 68% confidence is less than 50% of corresponding monthly energy-savings estimates except for December. For the annual energy-savings estimate, prediction uncertainty at 68% confidence is also less than 50% of the annual savings estimate. As seen from these results, the GP regression method can be used to determine compliance with uncertainty requirements. Other benefits of the method are also illustrated. Significantly, the GP method quantifies uncertainty in the estimated energy savings directly from the regression results without applying simplified statistical derivations. The method also quantifies and considers the uncertainty associated with both the pre-retrofit and the post-retrofit energy use data and model predictions, generating more comprehensive uncertainty estimates. In addition, GP regression provides "point-by-point" uncertainties for more detailed analysis of sparse data sets to attain balance between the confidence in results and the costs of collecting data.

Table 3. Monthly and Annual Energy Savings Prediction Uncertainty (% of Energy Savings at 68% Confidence)

1	2	3	4	5	6	7	8	9	10	11	12	Annual
49.2	43.8	43.4	36.7	34.8	36.5	47.1	46.5	32.3	34.8	41.8	51.5	37.4

Evaluating the Lengh of Data Collection

This section investigates whether GP modeling requires the data sets that cover the full seasonal variation in order to reliably predict annual energy use. In practice, M&V projects often confront limited, sparse datasets for analysis, and our case study also has limited data collected for the pre-retrofit period that does not cover the winter season. For validating GP models based on limited datasets, we compared two cases: (1) Case 1: developing a post-retrofit model using the dataset from May to August (the period used for developing the pre-retrofit model) and (2) Case 2: developing a post-retrofit model using the dataset obtained from February to October. Figure 3 displays the expected post-retrofit energy uses and associated 95% confidence intervals for Cases 1 and 2. For the summer and intermittent seasons, the two cases result in quite similar expected values with narrow confidence intervals. However, for the winter season, discrepancies between the two cases are observed in expected values, and Case 1 results have noticeably larger confidence intervals than Case 2. Indeed, Case 2 reduced the magnitude of uncertainty in annual energy-use predictions by 34%. This comparison suggests that collecting data points across all weather coditions is helpful to both improving the fit and reducing prediction uncertainty.

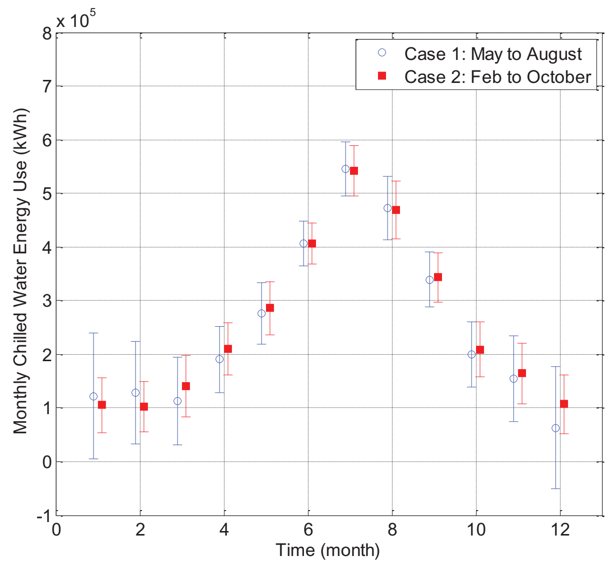


Figure 3 Monthly energy use predictions for case 1 (post-retrofit model with data from May to August) and case 2 (post-retrofit model with data from Feb to October)

CONCLUSION

M&V of energy savings are crucial to verifying whether energy-savings targets are met through implementation of EEMs. Conventional methods are limited in their capacity to consider multivariate interactions and to quantify uncertainty in predictions associated with data availability. In order to enhance the current practice, we have demonstrated a new M&V method based on GP modeling that is capable of capturing nonlinear trends, including hourly energy use behaviors, and accounting for multivariable interdependencies. In addition, since the GP model is formulated under a Bayesian setting, it can naturally quantify uncertainty in energy-savings predictions.

In order to enhance the applicability of GP modeling for M&V practices, we are developing: (1) GP regression software to calculate annual energy-savings estimates from different time-resolution data (i.e., hourly, daily, monthly); and (2) guidelines for handling different resolution data on the basis of broad case studies. Also, we need to directly compare the GP modeling method with conventional and new M&C statistical methods, using available datasets like those developed for the ASHRAE Predictor Shootout.

Further, the proposed method can be integrated in EMS for on-line analysis of energy savings and performance. In this application, the full capabilities of the methodology can be exercised productively to generate actionable information from the interval data collected in the EMS, including energy-savings reports and feedback to supervisory controls. For the special case of evaluating the energy savings from installing an EMS, the data collected by the system could be used to develop a post-retrofit model with uncertainty against which pre-retrofit energy use is statistically compared. In appropriate contexts, sampling strategies to collect pre-retrofit and post-retrofit data points by intermittent operations can generate energy-savings estimates with minimal number of baseline datapoints. Heo and Zavala (2012) evaluated adaptive sampling strategies and the effect of baseline data points on the performance of the GP model through simulation settings.

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