ANALYSIS OF COOLING REGRESSION MODELS FOR HOT AND HUMID CLIMATES BASED ON "OPERATIONAL EFFECTIVE ENTHALPY"

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ABSTRACT

Whole-building energy savings determination for energy efficiency projects is based on procedures established in the International Performance Measurement and Verification Protocol (IPMVP, 2012), specifically Option C. Energy use baseline models are developed from a regression analysis of the measured baseline data. These models generally use one or more independent variables, such as outdoor temperature, degree days, and/or occupancy. In practice, the most common variable that is used for these models is the outside air temperature (*OAT*). However, it has been observed that cooling model accuracy degrades when the latent load accounts for a significant proportion of the overall cooling load. Other studies have used the outside air enthalpy (*OAE*) to study the influence of outside air humidity on building energy analysis. Ji, et al. [2008], for example, used outside air enthalpy as an independent variable in the study of "Energy Balance Load" characteristics for screening building energy data.

Based on the physical cooling process in heating ventilation and air conditioning (HVAC) systems, a new variable called Operational Effective Enthalpy (*OEE*) is proposed to model cooling consumption. This paper shows that a chilled water regression model using *OEE* as the independent variable has a significantly lower coefficient of variation of the root mean square error (CV-RMSE) and a higher coefficient of determination (R^2) than a model based on either *OAT* or *OAE*. Examination of 12 case-study models and sensitivity analysis shows that for eight buildings with *OAT* CV-RMSE values ranging from 11.2% to 21.4%, *OEE* CV-RMSE values ranged from 5.8% - 9.0%. Corresponding R^2 ranges are 0.8829 – 0.9675 for *OAT* and 0.9655 – 0.9872 for *OEE*. The remaining four buildings where latent loads constitute a smaller fraction of total cooling load show a more modest improvement using *OEE* instead of *OAT*.

INTRODUCTION

The International Performance Measurement and Verification Protocol (IPMVP, 2012) Option C provides procedures to determine savings at the whole-facility level. One or more variables are usually used to determine a baseline model by regression analysis. Theoretically, all parameters which influence the building energy use should be included in a regression model. Since some of them are difficult to estimate in an actual building; they seldom appear explicitly as variables in regression models [Katipamula et al., 1998]. A number of studies have shown the benefit of multiple regression (MLR) analysis [Wu et al., 1992; Katipamula et al., 1994]. However, the most important environmental variables, such as outside air temperature, humidity and solar radiation, are often linearly related, which cause multicollinearity in the regression models as discussed by Ruch et al. [1993a] and Reddy et al. [1998]. Kissock et al. [1998] showed that the uncertainties of the regression coefficients may be so large that the model's usefulness for predicting purposes is compromised. In practice, the outside air temperature (*OAT*) is the most common variable used for inverse modeling. The *OAT* as the sole independent regression variable can adequately model energy consumption in residential building [Fels, 1986] and in some commercial buildings [Greely et al., 1990; Kissock et al., 1993, 1998; Ruch et al., 1992a, 1993b].

However, it has been found that some issues appear when *OAT* based regression models are applied on some buildings, especially for the chilled water energy consumption estimation. Figure 1 presents the plot of a typical pattern of chilled water consumption versus *OAT* for a building on the Texas A&M University campus in College Station, TX. In the plot, less linearity can be seen as the *OAT* increases since the latent cooling load cannot be represented totally by the *OAT*. This observation indicates that the models based on *OAT* might have an application limit. It could have an advantage when applied to a chilled water consumption dominated by sensible cooling. However, the model accuracy degrades when the latent load energy accounts for a significant proportion of the overall cooling load.

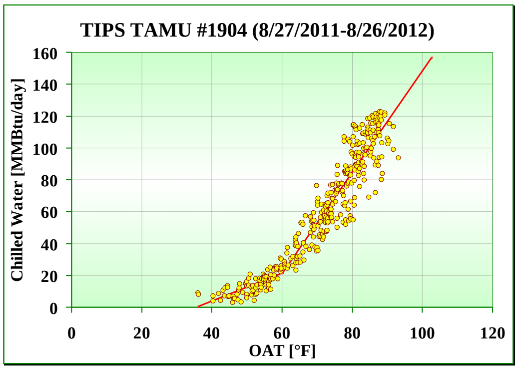


Figure 1. Plot of chilled water consumption vs. *OAT*

Outside air enthalpy (*OAE*) has been applied on “Energy Balance” for screening building energy data to study the influence of outside air humidity on building energy analysis [Ji et al., 2008; Masuda et al., 2009]. These studies showed that the energy balance load as a function of *OAE* has better linearity than that as a function of *OAT* in high temperature regions. Based on these results, this paper intends to further study and discuss the linear relationship of chilled water consumption as a function of *OAE* in hot and humid climates. Figure 2 presents a typical pattern of the building chilled water consumption as a function of the *OAE*. In high enthalpy regions, the model performance improves dramatically. The CV-RMSE of the *OAE* model decreased between 24% and 51% with an average of 37% in comparison to similar models based on *OAT*. However, the performance of *OAE* based regression model became worse in lower enthalpy regions.

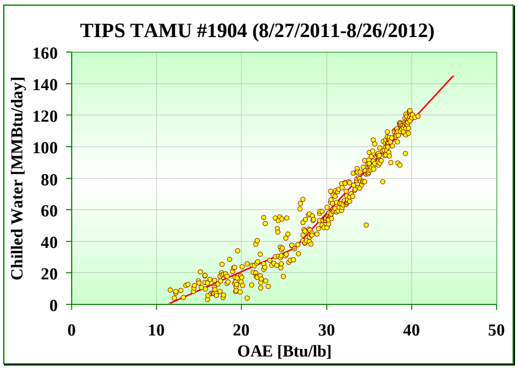


Figure 2. Plot of chilled water consumption vs. *OAE*

This pattern analysis showed that the chilled water regression model has less linearity in both high *OAT* and low *OAE* regions. In this study, a model performance improvement in all ranges of outside temperatures and enthalpies is proposed based on a new appropriate independent variable which relates the operational conditions of the air-handling units (AHU) and the outdoor conditions.

METHODOLOGY

Background of Cooling Process in HVAC Systems

In HVAC systems, air is typically cooled by passing it over a cooling coil. If the humidity ratio of mixed air is lower than that of conditioned space, only sensible cooling occurs. In this situation no latent load exists since dehumidification is not required except for the reduction of the dry-bulb outside air temperature. Otherwise, water from the air is condensed on the cooling coil and removed from the mixed air, producing latent load.

The moisture of mixed air consists of internal sources in the buildings and outdoor sources. The internal sources of moisture in the buildings include, among others, the respiration and transpiration from people and the evaporation from open water surfaces. Outdoor sources mainly come from outdoor air carried in by the HVAC system for ventilation. Reddy et al. [1995] clarified that the internal latent load contribution in most commercial buildings is usually smaller than that of the ventilation load even under low outdoor intake fractions –outdoor air fractions about 10% of the total building air flow. Additionally, the internal latent load is weather-independent. So it seems to be reasonable to treat internal latent load as a constant value related directly to the operation of the building, such as building type and occupancy. The internal latent load could be a constant value once the building is ready to operate and occupancy schedule is identified.

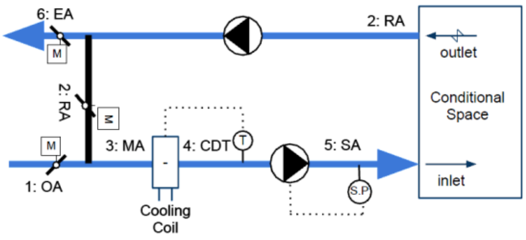


Figure 3. Schematic of SDVAV system

Figure 3 is a schematic representation of the main components of a single duct variable air volume (SDVAV) system. To avoid mold growth in the conditioned space and meet the human comfort needs, during the cooling process of a HVAC system the dehumidification occurs only when the mixed air go through from Point 3 to Point 4. The moisture of mixed air is the mix of return air and outside air –ventilation air. As it was discussed above, the moisture of return air from the internal source in the building is weather-independent and considered as a constant value. In this study, to simplify the analysis, the moisture carried in by the ventilation air at point 1 is assumed as the only source causing the change of latent load.

New Variable: Operational Effective Enthalpy

Based on the physical cooling process in HVAC systems, a new variable called "*Operational Effective Enthalpy* (*OEE*)" is proposed to model chilled water consumption, and it is defined as,

$$
\begin{aligned}
OEE = h_{OE} &= sensible\ enthalpy + (latent\ enthalpy - reference\ latent\ enthalpy)^{+} \\
&= h_{sen} + (h_{lat} - h_{ref,lat})^{+} \qquad (1)
\end{aligned}
$$

where, the $(\ )^{+}$ symbol indicate that the quantities in the parenthesis should be valid for positive values.

When $h_{lat} > h_{ref,lat}$, the latent load exits because the condensation occurs on the cooling coil, *OEE* is given by,

$$h_{OE} = h_{sen} + h_{lat} - h_{ref,lat} \qquad (2)$$

Otherwise, only sensible cooling takes place and no moisture removal occurs. Thus $(h_{lat} - h_{ref,lat})^{+} = 0$, *OEE* is given by,

$$h_{OE} = h_{sen} \qquad (3)$$

The reference latent enthalpy should be equal to the latent enthalpy at the air condition when latent loads began to appear.

The reference value can be estimated by analyzing the humidity control. ANSI/ASHRAE Standard 62–2010, Ventilation for Acceptable Indoor Air Quality, addresses the recommendations for humidity control: "Occupied space relative humidity shall be limited to 65% or less when system performance is analyzed with outdoor air at the dehumidification design condition (that is, design dew point and mean coincident dry-bulb temperatures) and with the space interior loads (both sensible and latent) at cooling design values and space solar loads at zero (Section 5.9.1)". The U.S. Environmental Protection Agency (EPA) presents a similar recommendation: "One way to help prevent mold is to maintain low indoor humidity, below 60 percent relative humidity, ideally 30–50 percent, if possible." Therefore, the cooling coil should be designed in such a way that the humidity ratio of air leaving the cooling coil is close to the middle of the allowable indoor air humidity ratio range [Reddy T.A. et al., 1995]. A typical cooling coil leaving air condition of 55°F (~13 °C) and 95% RH has a humidity ratio approximately equal to that of a zone conditioned at 74°F (24 °C) and 50% RH.

Besides the studies on the effect of the outside air humidity on the building energy use made by Ji et al. [2008] and Masuda, et al. [2009], Kissock et al. [1998] previously simulated hourly cooling coil load for constant air volume (CAV) and variable air volume (VAV) systems and found that there is a clear change-point at 55°F (~13 °C) where latent loads begin to appear. Therefore, the latent enthalpy value at 55°F and 95% RH was selected as reference latent enthalpy ($h_{ref,lat}$).

Change-Point Cooling Regression Model Using *OEE*

Change-point models typically combine search methods and least-square methods to find the best fitting model of segmented or piecewise linear regression. It identifies the change-point of an independent variable – either temperature, enthalpy, or as in this case, the operational effective enthalpy, the corresponding energy consumption at that change-point, and the slopes with the lowest square error over the selected sample. More studies about different forms and application of regression models have been discussed by Ruch et al. [1992a, 1992b, 1993b], Kissock et al. [1993, 1998] and Reddy et al. [1997a, 1997b]. The general description for these models could be the four-parameter (4P) model which is expressed as following:

$$E_c = \beta_1 - \beta_2 (\beta_4 - X)^+ + \beta_3 (X - \beta_4)^+ \qquad (4)$$

where X is any independent variable, either temperature or enthalpy for example.

When $\beta_2 = 0$, the four-parameter model will be simplified to three-parameter model as equation (5).

$$E_c = \beta_1 + \beta_3 (X - \beta_4)^+ \qquad (5)$$

Adapting the change-point models to include the *OEE* in the energy estimation methodologies, the expressions become

$$E_c = \beta_1 - \beta_2 (\beta_4 - h_{OE})^+ + \beta_3 (h_{OE} - \beta_4)^+ \qquad (6)$$

When $h_{lat} > h_{ref,lat}$, the latent load exits because the condensation occurs on the cooling coil, thus

$$E_c = \beta_1 - \beta_2 [\beta_4 - (h_{sen} + h_{lat} - h_{ref,lat})]^+ + \beta_3 [(h_{sen} + h_{lat} - h_{ref,lat}) - \beta_4)]^+ \qquad (7)$$

Otherwise, only sensible cooling takes place and no moisture removal occurs. Thus $(h_{lat} - h_{ref,lat})^+ = 0$, the *OEE* change-point model is,

$$E_c = \beta_1 - \beta_2 (\beta_4 - h_{sen})^+ + \beta_3 (h_{sen} - \beta_4)^+ \qquad (8)$$

Models of equation (7) and equation (8) can be combined into a single regression model using an indicator variable, *I*.

$$E_c = \beta_1 - \beta_2 \{\beta_4 - [h_{sen} + I(h_{lat} - h_{ref,lat})]\}^+ + \beta_3 \{[h_{sen} + I(h_{lat} - h_{ref,lat}) - \beta_4]\}^+ \qquad (9)$$

When $h_{lat} > h_{ref,lat}$, $I=1$, the cooling energy consumption is given by equation (7). Otherwise, I=0, the cooling energy consumption is given by equation (8).

APPLICATION OF *OEE* COOLING REGRESSION MODEL

For testing purposes the *OEE* regression model was applied to estimate the cooling energy consumption for twelve buildings at Texas A&M University. The criterion used to select the most appropriate model is to maximize the goodness-of-fit using the simplest model or combination of models [Draper and Smith 1981]. In this study, the coefficient of variation of the root-mean-square error (CV-RMSE) and coefficient of determination (R^2) are used. The R^2 and CV-RMSE for *OAT*, *OAE*, and *OEE* models for the analyzed twelve buildings are listed in Table 1.

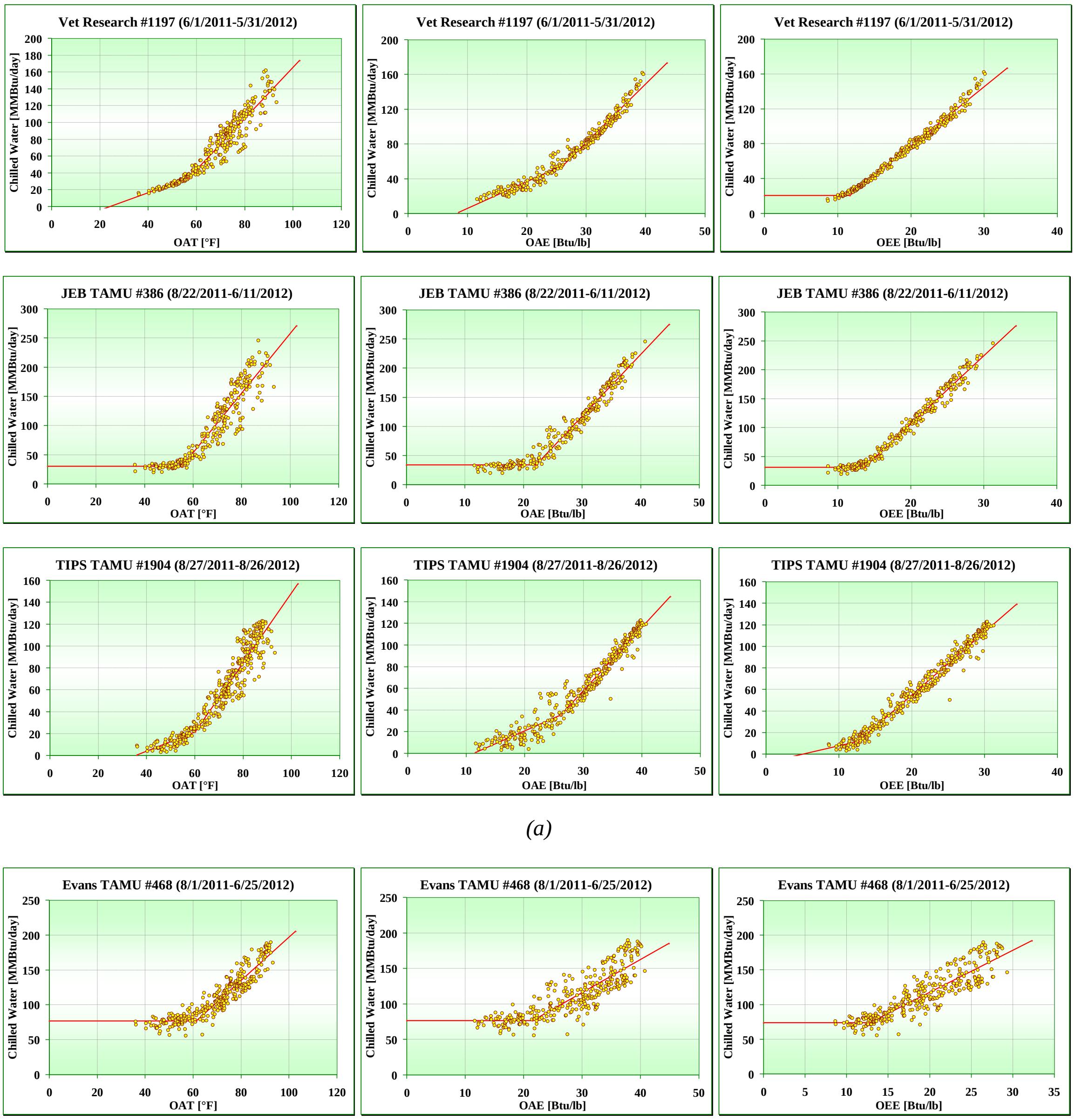
Compared to *OAT* and *OAE* base regression models, the *OEE* base models statistical indices have dramatically improved for eight buildings and kept in the same level for the other four buildings as shown in Figure 4(a) and (b), respectively.

For eight buildings, the chilled water regression models using *OEE* as the independent variable had a significant improvement in all temperatures regions, compared to the models based on *OAT*. The CV-RMSE values decreased between 33% and 62%, with an average reduction of 51%. The models based on *OEE* also showed an improvement with respect to models based on *OAE*, on the order of 9% to 31%, with an average decrease of 22%. Similar trends were obtained for the coefficient of determination (R^2). Though, for four buildings no improvement on either CV-RMSE or R^2 was observed with the application of *OEE* model, showing that there is certain limit of application on this approach.

The *OAE* and *OEE* parameters were introduced into the cooling energy consumption modeling in order to solve the problem caused by latent load. As described previously the latent load is mainly from the ventilation latent load. Therefore, the application of *OEE* cooling regression modeling has its major advantage when is applied on buildings with large outside air intake fractions in hot and humid climates.

Table 1. Models statistic parameters using outside air temperature, enthalpy, and operational effective enthalpy as independent regression variable for twelve buildings of Texas A&M University

Building List	***OAT* Model**		***OAE* Model**		***OEE* Model**	
	R^2	CV-RMSE	R^2	CV-RMSE	R^2	CV-RMSE
#1811 Vet Med Research Addition	0.9139	18.0%	0.9785	8.9%	0.9872	6.9%
#1530 Interdisciplinary Life Science	0.9372	11.2%	0.9633	8.5%	0.9779	6.6%
#1197 Vet Research Building	0.9083	15.5%	0.9739	8.2%	0.9868	5.8%
#1085 Small Animal Hospital	0.9111	12.6%	0.9588	8.6%	0.9655	7.8%
#1507 Bio-Bio	0.9105	21.4%	0.9718	12.0%	0.9864	8.3%
#1904 TIPS	0.9115	17.6%	0.9569	12.3%	0.9768	9.0%
#386 Jack E. Brown	0.8829	20.1%	0.9637	11.2%	0.9819	7.9%
#376 Chemistry Building Addition	0.9675	13.0%	0.9824	9.6%	0.9853	8.7%
#468 Evans Library	0.8763	10.4%	0.7520	14.7%	0.8144	12.7%
#682 Wisenbaker	0.8917	15.8%	0.8630	17.8%	0.8958	15.5%
#1560 Student Rec Center	0.9240	12.4%	0.8788	15.7%	0.8962	14.5%
#1194 Large Animal Hospital	0.9572	11.2%	0.9565	11.3%	0.9658	10.0%



(a)

(b)

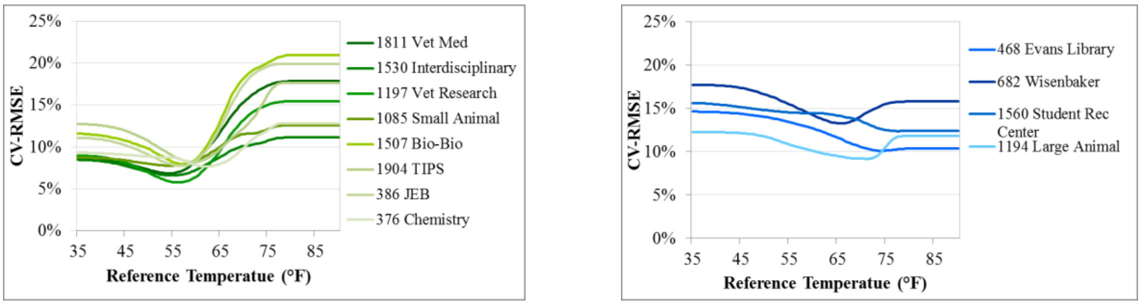
Figure 4. Chilled water consumption models for the buildings sample as a function of the *OAT*, *OAE* and *OEE*.

SENSITIVITY ANALYSIS

To further study the influence of the reference latent enthalpy on the model stability, an analysis with the different reference latent enthalpy was carried out, still keeping the relative humidity of cooling coil at 95%. The change of reference temperature in the range 35°F to 90°F was analyzed. Figure 5(a) presents the change in CV-RMSE with the reference temperature for the eight buildings, which *OEE* base models have dramatic improvement. The result shows that the reference temperature with minimum CV-RMSE is in the range of 54°F to 62°F as shown in Table 2.

The difference between the minimum CV-RMSE and CV-RMSE with reference conditions of 55°F, 95RH is less than 1%. This result indicates that it is appropriate to select latent enthalpy with 55°F, 95 RH as the reference latent enthalpy and the *OEE* regression model is stable.

Figure 5(b) presents the change in CV-RMSE with the reference temperature for the four buildings that the *OEE* base models have no improvement. The result shows that the minimum CV-RMSE appears at the high reference temperature, greater than 66°F. This indicates that the ventilation latent load might not account for a significant proportion of the overall cooling load. The designed outdoor intake fractions for the buildings in Figure 5(b) are below 15%. This fraction is much lower than that of buildings shown in Figure 5(a). The designed outdoor intake fractions for some buildings in Figure 5(a) are even higher than 80%. Confirming that the *OEE* cooling regression model has its major advantage when is applied on buildings with the large outdoor intake fractions in hot and humid climates.



(a) *(b)*

Figure 5. Sensitivity analysis for the variation of the reference temperature with 95% RH, for the twelve buildings sample.

Table 2. Optimal OEE models statistic parameters, corresponding reference temperature and humidity ratio for twelve buildings in Texas A&M University.

Building List	**CV-RMSE$_{min}$**	**R^2 with CV-RMSE$_{min}$**	**T$_{ref}$ with CV-RMSE$_{min}$**	**w (lb/lb) with CV-RMSE$_{min}$**
#1811 Vet Med Research Addition	6.8%	0.9874	54.0	0.0084
#1530 Interdisciplinary Life Science	6.6%	0.9777	55.0	0.0087
#1197 Vet Research Bldg	5.8%	0.9936	56.0	0.0091
#1085 Small Animal Hospital	7.8%	0.9792	54.5	0.0086
#1507 Bio-Bio	7.9%	0.9874	57.0	0.0094
#1904 TIPS	8.2%	0.9805	59.5	0.0103
#386 Jack E. Brown	7.7%	0.9848	57.0	0.0094
#376 Chemistry Building Addition	7.7%	0.9942	62.0	0.0113
#468 Evans Library	10.1%	0.8906	74.0	0.0172
#682 Wisenbaker	13.2%	0.9278	66.0	0.0130
#1560 Student Rec Center	12.4%	0.9237	77.5	0.0194
#1194 Large Animal Hospital	9.2%	0.9718	71.0	0.0155

Note: OEE reference temperature is associated to a 95% RH.

CONCLUSIONS

Based on the physical performance of the cooling process in HVAC systems, a new variable called Operational Effective Enthalpy (*OEE*) was proposed to model building chilled water consumption. Examination of 12 case-study models and sensitivity analysis showed that for eight buildings the chilled water regression models using *OEE* as the independent variable has a significant improvement in all temperatures regions, compared to the models based on *OAT*, the CV-RMSE decreased between 33% and 62%, with an average decrease of 51%. The models based on *OEE* also showed an improvement with respect to models based on *OAE*, on the order of 9% to 31%, with an average decrease of 22%. Similar trends were obtained for the coefficient of determination (R^2). The remaining four buildings where latent loads constitute a smaller fraction of total cooling load show a more modest improvement using *OEE* instead of either *OAT* or *OAE*. These results indicate the application of *OEE* cooling regression modeling could have a major advantage when it is applied on buildings with large outside air intake fractions in hot and humid climates.

ACKNOWLEDGMENTS

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REFERENCES

ASHRAE, 2010, ANSI/ASHRAE Standard 62-I–2010, *Ventilation for Acceptable Indoor Air Quality. American Society of Heating, Refrigerating and Air-Conditioning Engineers*, Atlanta, GA.

Draper, N., and H. Smith, 1981, *Applied regression analysis*, 2nd ed. New York: John Wiley and Sons.

Fels, M. (Ed), 1986, Special Issue Devoted to Measuring Energy Savings, the Princeton Scorekeeping Method (PRISM*), Energy and Buildings*, Vol. 9, No. 1 and 2.

Greely, K., Harris, J., and Hatcher, A., 1990, Measured Savings and Cost-effectiveness of Conservation Retrofits in Commercial Buildings, *Lawrence Berkeley Laboratory Report-27586*, Berkeley, CA.

IPMVP 2012, *The International Performance Measurement and Verification Protocol*: *Concepts and Options for Determining Energy and water savings Volume 1,*Chapter 4, pp. 25-28..

Ji, J., Baltazar, J.C. and Claridge, D.E., 2008, Study of the Outside Air Enthalpy Effects in the Screening of Metered Building Energy Data, *The 16th Symposium on Improving Building Systems in Hot and Humid Climates*, Plano, TX. December.

Katipamula, S., Reddy, T. A., Claridge, D.E., 1994, Development and Application of Regression Models to Predict Cooling Energy Consumption in Large Commercial Buildings. *ASME/JSME/JSES International Solar Energy Conference, San Francisco, California*, March, pp. 307-322.

Katipamula, S., Reddy, T. A., Claridge, D.E., 1998, Multivariate Regression Modeling. *Journal of Solar Energy Engineering, Transactions of the ASME*, Vol. 120, pp. 177-184.

Kissock, J. K., Reddy, T. A., Fletcher, D., and Claridge, D. E., 1993, The Effect of Short Data Periods on the Annual Prediction Accuracy of Temperatures-Dependent Regression Models of Commercial Buildings Energy Use, *Proceedings of the 1993 ASME/ASES/SED International Solar Energy Conference*, Washington, D.C., April, pp. 455-463.

Kissock, J. K., Reddy, T. A., Claridge, D.E., 1998, Ambient-Temperature Regression Analysis for Estimating Retrofit Savings in Commercial Buildings, *Transactions of the ASME*, Vol. 120, pp. 168-176.

Masuda, H., Ji, J., and Baltazar, J.C., 2009, Use of First Law Energy Balance as a Screening Tool for Building Energy Use Data: Experiences on the Inclusion of Outside Air Enthalpy Variable. *Proceedings of the Ninth International Conference for Enhanced Building Operations*, Austin, Texas, November.

Ruch, D., and Claridge, D.E., 1992a. A Four Parameter Change-point Model for Predicting Energy Consumption in Commercial Buildings. *Journal of Solar Energy Engineering, ASME Transactions*, Vol.114, pp. 77-83.

Ruch, D., and Claridge, D.E., 1992b. NAC for Linear and Change-point Linear Building Energy Models. *ACEEE 1992 Summer Study on Energy Efficiency in Buildings*, pp. 3,263-3,273.

Ruch, D., Kissock, J. K., and Reddy, T. A., 1993a, Model Identification and Prediction Uncertainty of Linear Building Energy Use Models with Autocorrelated Residuals. *Proceedings of the ASME-SED Conference*, Washington, DC, Apr.

Ruch, D., and Claridge, D.E., 1993b. A Development and Comparison of NAC Estimates for Linear and Chang-point Linear Energy Models for Commercial Buildings. *Energy and Buildings*, Vol.20, pp.87-95.

Reddy, T.A., Katipamula S., Kissock J.K., et al, 1995, The Functional Basis of Steady-state Thermal Energy Use in Air-side HVAC Equipment, *Journal of Solar Energy Engineering*, Vol. 117, pp.31-39.

Reddy, T.A., Saman N.F., and Claridge D.E., et al. 1997a, Baseline methodology for facility-level monthly energy use-Part 1: Theoretical aspects. *ASHRAE Transactions*.Vol.103, pp. 336-347.

Reddy, T.A., Saman, N.F., and Claridge, D.E., et al., 1997b, Baseline Methodology for Facility-level Monthly Energy Use-Part 2: Theoretical aspects. *ASHRAE Transactions*.Vol.103, pp. 348-359.

Reddy, T. A., Kissock, K., and Ruch, D., 1998. Uncertainty in Baseline Regression Modeling and In Determination of Retrofit Savings. *ASME Journal of Solar Energy Engineering*, Vol. 120, No. 3.

The United States Environmental Protection Agency (EPA), 2008, *Mold Remediation in schools and Commercial Buildings*, pp.3.

Wu, J., Reddy, T.A., and Claridge, D.E., 1992. Statistical Modeling of Daily Energy Consumption in Commercial Buildings using Multiple Regression and Principal Component Analysis. *Proceedings of the eighth symposium on Improving Building System in Hot and Humid Climates*, Dallas, TX, May.