IDENTIFICATION OF THE ELECTRIC CHILLER MODEL FOR THE ENERGYPLUS PROGRAM USING MONITORED DATA IN AN EXISTING COOLING PLANT

Danielle Monfet, and Radu Zmeureanu
Centre for Building Studies, Department of Building, Civil and Environmental Engineering,
Faculty of Engineering and Computer Science
Concordia University, Montréal, Québec, CANADA

ABSTRACT

This paper proposes an approach to identify the coefficients of the chiller model used by the EnergyPlus program. Data collected every 15 minutes from an existing cooling plant are used to evaluate the approach. The results demonstrate that 28-days of data for the first chiller and 7-days of data for the second chiller, collected at the beginning of the summer season, are sufficient to obtain accurate prediction of the electric power input to chillers over the summer season: the CV(RMSE) are 3.7% and 4.9% for the electric power input, respectively, for the first and the second chiller over the training data set used to identify the model coefficients. For the remainder of the summer season, the CV(RMSE) is below 7.6%.

INTRODUCTION

The use of simulation is becoming more common to assess the operating energy performance and to identify operating issues in buildings. Different studies have demonstrated the use of calibrated simulation models to identify opportunities to improve the whole building energy performance (e.g. Pan et al. 2007, Lawrence and Braun. 2007, Lee et al. 2007). The calibration of the model is a complex process and often the lack of manufacturer and as-operated equipment performance data leads to discrepancies between the simulation results and measured data.

Chillers consume a large amount of electricity to prepare the chilled water needed by the HVAC systems in large commercial and institutional buildings. Thus, it is important to develop accurate simulation models that characterize their operation. Simulation tools often use default performance curves to help users evaluate the electric power input to the chillers. Often though, the chillers used in buildings are different than the default equipment. The user has the option to develop and implement more appropriate performance curves in the simulation tool. A few approaches have been proposed to identify model coefficients for chillers by using manufacturer data (Lebrun et al. 1994) or laboratory data or curve shifting using short-term measurements that cover the full range of values of independent variables (e.g., evaporator part-load ratio) used in such a model (Hydeman and Gillespie 2002 and Hydeman et al. 2002). However, it is not always possible to have access to detailed manufacturer or laboratory data to apply the approach presented in the literature. In order to address this issue, a new approach using monitored data collected via the Monitoring and Data Acquisition System (MDAS) is proposed to identify the coefficients of one of the EnergyPlus models that characterise the performance of a water-cooled electric chiller. This approach is an extension of the Hydeman and Gillespie (2002) method, which is based on Hydeman et al. (2002). Data monitored over the summer 2009 season for two chillers of 3165 kW (900 tons) each, with different operating part-loads, duration of daily operation and return chilled water temperature from the building are used to evaluate the proposed approach. Also, the proposed approach is evaluated for different data set sizes to identify the minimum training set size required to identify the coefficients that accurately estimate the electric power input to the chiller.

PROPOSED APPROACH

The approach is applied to one of the models used by the EnergyPlus program (DOE 2009) to estimate the electric power input of an electric liquid chiller.

Description of the model

The selected EnergyPlus model simulates the electric power input (P_E) of an electric liquid chiller based on the chilled water supply temperature (T_{CHWS}), the temperature leaving the condenser (T_{CNDS}) and the evaporator load (Q_E). The chiller power input (P_E), in kW, is determined using Equation (1).

$$P_E = (Q_{avail}) \cdot (1/COP_{ref}) \cdot (EIRFTemp) \cdot (EIRFPLR) \quad (1)$$

where, Q_{avail} is the available cooling capacity of the chiller in kW, defined by Equation (2);

$$Q_{avail} = Q_{ref} \cdot (CapFTemp) \quad (2)$$

where Q_{ref} is the chiller capacity at reference conditions (reference temperatures and flow rates defined by the user); *CapFTemp* is the cooling capacity factor for different operating temperatures, given by Equation (3);

COP_{ref} is the reference coefficient of performance;

EIRFTemp is the energy input to cooling output ratio at full load, given by Equation (4);

EIRFPLR is the energy input to cooling output ratio at part load ratio, given by Equation (5).

The model, developed by Hydeman et al. (2002) as part of the CoolTools™ project sponsored by Pacific Gas and Electric Company (PG&E), uses Equations (3) to (5) to determine the various coefficients used in the chiller power Equation (1).

$$CapFTemp = a_0 + (a_1 \cdot T_{CHWS}) + (a_2 \cdot T_{CHWS}{}^2) + (a_3 \cdot T_{CNDS}) + (a_4 \cdot T_{CNDS}{}^2) + (a_5 \cdot T_{CHWS} \cdot T_{CNDS}) \quad (3)$$

$$EIRFTemp = b_0 + (b_1 \cdot T_{CHWS}) + (b_2 \cdot T_{CHWS}{}^2) + (b_3 \cdot T_{CNDS}) + (b_4 \cdot T_{CNDS}{}^2) + (b_5 \cdot T_{CHWS} \cdot T_{CNDS}) \quad (4)$$

$$EIRFPLR = c_0 + (c_1 \cdot T_{CNDS}) + (c_2 \cdot T_{CNDS}{}^2) + (c_3 \cdot PLR) + (c_4 \cdot PLR^2) + (c_5 \cdot T_{CDNS} \cdot PLR) + (c_6 \cdot PLR^3) \quad (5)$$

where *PLR* is the part-load calculated using Equation (6).

$$PLR = \frac{Q_E}{Q_{avail}} \quad (6)$$

The coefficients of the performance curves (Equations (3) to (5)) can either be generated using manufacturer's data or measured data. In this study, the Hydeman and Gillespie (2002) technique, which is based on Hydeman et al. (2002), is used with some modifications for the identification of the coefficients a_j, b_j, and c_j.

Initial training set

The training data set contains monitored data at each time-step of the following variables: P_E, Q_E, *COP*, T_{CHWS}, T_{CHWR}, T_{CNDS}, and T_{CNDR}, where P_E is the instantaneous electric power input; Q_E is the instantaneous chilled water load, equal to the evaporator load determined using the formulation presented in ASHRAE 2002; *COP* is the coefficient of performance equal to Q_E/P_E, dimensionless; T_{CHWS} is the supply chilled water temperature; T_{CHWR} is the return chilled water temperature; T_{CNDR} is the return condenser water temperature from the cooling tower; and T_{CNDS} is the condenser water leaving temperature to the cooling tower.

1. In the training data set, the maximum evaporator load Q_{Emax} is identified. The maximum Q_{Emax} and the corresponding electric power P_{Emax}, and *COP* are then used as the reference values ($Q_{ref} = Q_{Emax}$, $P_{ref} = P_{Emax}$, and COP_{ref}) in the modified approach, which is proposed in this study;
2. For all data in the training data set, the *CAPFT* is calculated using Equation (7), where $Q_{ref} = Q_{E,max}$ and Q_E is the evaporator load at each time-step;

$$CAPFT = \frac{Q_E}{Q_{ref}} \quad (7)$$

3. The training data set is split into (1) full-load and (2) part-load conditions based on the *CAPFT* values calculated using Equation (7). For this study, the full-load conditions data set was selected for *CAPFT* values greater than or equal to 0.85 ($CAPFT \geq 0.85$), while the part-load conditions for *CAPFT* values were lower than 0.85 ($CAPFT < 0.85$). A *CAPFT* greater than 0.85 is selected for the full-load conditions since the chillers operate most of the time around 55-60% of their full design capacity.

Full-load conditions data set (CAPFT ≥ 0.85)

4. For the full-load conditions data set ($CAPFT \geq 0.85$), the *EIRFT* is calculated at each time-step using Equation (8), where *CAPFT* is calculated using Equation (7);

$$EIRFT = \frac{P_E}{P_{ref} \cdot CAPFT} \quad (8)$$

5. The full-load conditions data set is used to identify the coefficients a_j of Equation (3) where *CapFTemp* is equal to *CAPFT* (Equation (7)), and the coefficients b_j of Equation (4) where *EIRTemp* is equal to *EIRFT* (Equation (8)).

Full-load and part-load conditions data set

6. Using the coefficients a_j and b_j identified in (5), the estimates of *CapFTemp** (Equation(3)) and *EIRTemp** (Equation (4)) are calculated for all the data in the training data set, i.e. for the full- and part-load conditions;
7. The *PLR* (Equation (6)) and *chillerEIRFLPR* (Equation (9)) are calculated for all the data in the training data set, i.e. for the full- and part-load conditions, where *CapFTemp** is the estimate of *CapFTemp* and *EIRTemp** is the estimate of *EIRTemp*;

$$chillerEIRFPLR = P_E/(P_{ref} \cdot CapFTemp^* \cdot EIRTemp^*) \quad (9)$$

8. All the data in the training data set are used to identify the coefficients c_j of Equation (5), where *EIRFPLR* is equal to *chillerEIRFLPR* (Equation (9));
9. Using the coefficients c_i identified in (8), *EIRFPLR** (Equation (5)) is estimated for all the data in the training data set, i.e. for the full- and part-load conditions;
10. The electric power input to the chiller (Equation (1)) is calculated for all data points with the variables calculated in (6), *CapFTemp** and *EIRTemp**, and in (9), *EIRFPLR**.

DEVELOPMENT OF THE MODELS FOR THE CSB CHILLERS

Chillers installed at the Concordia Sciences Building (CSB) of Concordia University are used to evaluate the proposed approach and the requirements in terms of training data set size. Two centrifugal chillers from the same manufacturer, CH1 and CH2, use R-123 refrigerant, have the cooling capacity of 3165 kW (900 tons) each, and the coefficient of performance (COP) of 5.76 at design conditions.

Information about the as-built and as-operated thermal performance of the CSB is obtained through the collaboration of the Physical Plant of Concordia University from the Monitoring and Data Acquisition System (MDAS). The system uses a leading controls manufacturer's DDC control system. Monitored data for the summer 2009, from June 22 to September 20, are selected to analyze the operating characteristics of the chillers. The accuracy of the monitored electric power input is 5% of the recorded data.

Table 1 presents the monitored operating characteristics of the chillers used in this case study for the summer 2009.

Table 1
Average operating characteristics of chillers, summer 2009

ITEM	CH1	CH2
T_{CHWS}, °C	6.8 ± 0.4	6.7 ± 0.2
T_{CHWR}, °C	11.3 ± 1.5	11.2 ± 1.3
T_{CNDR}, °C	28.3 ± 0.4	28.5 ± 0.4
T_{CNDS}, °C	33.3 ± 1.8	33.3 ± 1.6
Q_E, kW	1671 ± 549	1615 ± 477
P_E, kW	313 ± 92	299 ± 77
COP	5.29 ± 1.0	5.39 ± 1.3
No. operating hours	1299	663
Electricity use, kWh	406,155	198,330

Monitored data pre-processing

Prior to identifying the model coefficients, a detailed analysis of the monitored data is performed to identify any data monitoring problems or outliers. This includes removing any set of monitored data that is incomplete at a specific time-step; and outliers, which are measurements satisfying the conditions of Equations (10a) and (10b), where y_i is the measured value, y_{mean} is the mean of the measured values in the data set, and σ is the standard deviation.

$$y_i < (y_{mean} - 3 \cdot \sigma) \qquad (10a)$$

$$y_i > (y_{mean} + 3 \cdot \sigma) \qquad (10a)$$

Selection of training and testing data sets

The data set selected from monitored data that is used to identify the model coefficients is divided in two sub-sets: (1) a training data set and (2) a testing data set. Different methods of dividing the selected data set into training and testing data sets (e.g., random selection) can be considered. For this study, the training data set uses the first two-thirds of the model data set (Kreider et al. 1994) to identify the model coefficients, and the testing data set uses the balance of the data set to verify the correctness of the model before it is used.

The first abbreviation of the set name indicates the equipment for which the model is developed, for example, CH1 for chiller no.1. The second abbreviation in the set name indicates the length of data set, for example 7D for seven days. The starting and ending date of each data set is given for both training and testing data sets (Table 2). The data set size indicates the number of time-steps, of 15-minute each, available for each data set.

From June 22 to July 6 2009, the chiller CH2 is the first chiller to be started-up, while after July 6 2009, the chiller CH1 becomes the first chiller to be started-up, when required. Since the quantity of monitored data during operation is different at the beginning of the summer, the first data for chiller CH1 is composed of 30 hours (CH1-30H), while for chiller CH2 is composed of one day (CH2-1D). Table 2 presents the 12 data sets used for the training and testing of the model.

RESULTS AND DISCUSSION

The proposed approach is illustrated using the data of 28 days for chiller CH1. The results are then presented for the different data sets size used to develop the models for both chillers CH1 and CH2.

Example of identification of the model

A sample of data for the CH1-28D data set is presented in Table 3. The results for the calculations performed on the full-load conditions are presented in Table 3 and for the full- and part-load conditions in Table 4, while the identified coefficients are presented in Table 5.

The proposed approach is used to identify the coefficients of the performance curves for the electric power input to the chiller.

<u>Initial training set</u> (Table 3)

1. The maximum evaporator load Q_{Emax} =2666 kW is identified at 07/21 12:45 (bold values in Table 3); therefore $Q_{ref} = Q_{Emax}$ = 2666 kW, P_{ref} = 517 kW, and COP_{ref} = 5.157 .
2. $CAPFT$ is calculated using Equation (7). For example, at 12:00 on 07/21:

$$CAPFT = \frac{Q_E}{Q_{ref}} = \frac{2546\ kW}{2666\ kW} = 0.955 \qquad (11)$$

3. The training data set is split into (1) full-load conditions (FL), where $CAPFT \geq 0.85$ and (2) part-load conditions (PL), where $CAPFT < 0.85$.

<u>Full-load conditions data set</u> (Table 3)

4. For the full-load conditions data set ($CAPFT \geq$ 0.85), the $EIRFT$ is calculated at each time-step

using Equation (8). For example, at 12:00 on 07/21:

$$EIRFT = \frac{P_E}{P_{ref} \cdot CAPFT} = \frac{497}{517 \cdot 0.955} = 1.0066 \quad (12)$$

5. The coefficients a_j of Equation (3), and the coefficients b_j of Equation (4) are identified using the calculated CAPFT and EIRFT, respectively, along with measurements of temperatures (Table 3). The identified coefficients a_j and b_j for both chillers CH1 and CH2 are presented in Table 5, and compared with the default values of a TRANE chiller, as presented in the EnergyPlus program.

Full-load and part-load conditions data set (Table 4)

6. Using the coefficients a_j and b_j, the estimates of *CapFTemp** (Equation(3)) and *EIRTemp** (Equation (4)) are calculated for all the data in the training data set. For example, at 12:00 on 07/21 , *CapFTemp** = 0.9577033 and *EIRTemp** = 0.9902288.
7. The *PLR* (Equation (6)) and *chillerEIRFLPR* (Equation (9)) are calculated for all the data in the training data set. For example, at 12:00 on 07/21 , the PLR = 0.99716 and

$$chillerEIRFPLR = \frac{497}{(517 \cdot 0.9577033 \cdot 0.9902288)} = 1.01368 \quad (13)$$

8. The coefficients c_j of Equation (5) are identified (Table 5) by using *EIRFPLR* equal to *chillerEIRFLPR*, along with the calculated PLR and measurements of temperatures.
9. Using the coefficients c_i identified in (8), *EIRFPLR** (Equation (5)) is estimated for all the data in the training data set. For example, at 12:00 on 07/21 , *EIRFPLR** = 0.98197.
10. The electric power input to the chiller (Equation (1)) is calculated for all data points with the *CapFTemp**, *EIRTemp**, *EIRFPLR**. For example, at 12:00 on 07/21 :

$$P_E = (2666 * 0.9577033) \cdot (1/5.157) \cdot (0.9902288) \cdot (0.98197) = 481 \text{ kW} \quad (14)$$

Table 2
Training and testing data sets

ITEM	TRAINING SET		TESTING SET	
	DATE	DATA SET SIZE	DATE	DATA SET SIZE
CH1-30H	06/22 to 06/26 – 22.5 h	85	06/27 to 07/06 – 8 h	29
CH1-7D	06/22 to 07/10	331	07/11 to 07/12	186
CH1-10D	06/22 to 07/12	517	07/13 to 07/15	94
CH1-14D	06/22 to 07/15	610	07/16 to 07/19	227
CH1-21D	06/22 to 07/19	822	07/20 to 07/26	608
CH1-28D	06/22 to 07/24	1271	07/25 to 08/02	822
CH2-1D	06/22 0:00 to 16:00	47	06/22 16:00 to 24:00	32
CH2-7D	06/22 to 06/26	443	06/27 to 06/28	192
CH2-10D	06/22 to 06/27	538	06/28 to 07/01	380
CH2-14D	06/22 to 06/30	833	07/01 to 07/05	400
CH2-21D	06/22 to 07/05	1233	07/06 to07/12	91
CH2-28D	06/22 to 07/10	1336	07/11 to 07/19	49

Table 3
Sample of data and calculation of training set for CH1-28D, July 21 2009

		T_{CHWS}, °C	T_{CNDS}, °C	Q_E, kW	P_E, kW	COP	CAPFT	FL	PL	EIRFT
DATE	**TIME**	**MEASUREMENTS**					**CALCULATIONS**			
7/21	12:00	6.72	36.66	2546	497	5.123	0.955	X		1.0066
7/21	12:15	6.72	36.55	2586	505	5.121	0.970	X		1.0070
7/21	12:30	6.72	37.05	2568	481	5.339	0.963	X		0.9659
7/21	**12:45**	**6.72**	**36.89**	**2666**	**517**	**5.157**	1.000	X		1.0000
7/21	13:00	6.78	36.83	2644	511	5.175	0.992	X		0.9965
	⋮									
7/21	20:00	6.72	35.66	2346	445	5.272	0.880	X		0.9781
7/21	20:15	6.78	35.33	2280	435	5.243	0.855	X		0.9836
7/21	20:30	6.78	34.94	2200	419	5.252	0.825		X	
7/21	20:45	6.72	35.5	2244	420	5.344	0.842		X	
7/21	21:00	6.67	35.22	2262	421	5.374	0.849		X	

Table 4
Sample of calculation for training set of CH1-28D, July 21 2009

DATE	TIME	*CAPFTemp**	*EIRTemp**	*PLR*	*chillerEIRFLPR*	*EIRFPLR**	$P_{chiller}$, *kW*
7/21	12:00	0.9577033	0.9902288	0.99716	1.01368	0.98197	481
7/21	12:15	0.9487055	0.9882193	1.02243	1.04188	1.01906	494
7/21	12:30	0.9931338	0.9959175	0.96982	0.94064	0.93934	480
7/21	12:45	0.9779322	0.9938546	1.02257	1.02889	1.01168	508
7/21	13:00	0.9755892	0.9980719	1.01663	1.01508	1.00464	506
	⋮						
7/21	20:00	0.8920124	0.9654081	0.98647	0.99951	0.98965	440
7/21	20:15	0.8714134	0.9676649	0.98161	0.99781	0.99049	431
7/21	20:30	0.8576679	0.9543319	0.96235	0.99016	0.97481	412
7/21	20:45	0.8848609	0.9600703	0.95127	0.95627	0.95004	417
7/21	21:00	0.8816749	0.9368144	0.96245	0.98589	0.96905	413

Table 5
Example of coefficients for the electric power input models for chillers

ITEM	CH1-28D	CH2-7D	TRANE
a_0	55.6849	11.9917	-0.2176
a_1	-5.9214	-7.7791	-0.0494
a_2	0.13986	0.71449	8.70 E-05
a_3	-1.98856	0.86498	0.09612
a_4	0.01810	-0.00760	-0.00203
a_5	0.11092	-0.05142	0.00254
b_0	-42.7144	-51.5804	-0.0199
b_1	6.25958	22.43780	-0.07848
b_2	-0.19697	-2.30418	0.00194
b_3	1.19876	-1.34114	0.07123
b_4	-7.36280 E-03	-3.78277 E-03	-9.17380E-04
b_5	-0.09546	0.24441	-0.00058
c_0	1.94517	2.33977	0.35161
c_1	-0.01389	-0.08433	0.00921
c_2	-1.49532 E-03	6.53170 E-04	-2.382325E-05
c_3	-1.91033	-1.91995	0.12232
c_4	-1.53332	-0.10428	-0.18201
c_5	0.12419	0.07856	-0.00784
c_6	0.46424	0.03295	0.68849

Different criteria are used to evaluate the performance of different training sets. The Coefficient of Variance of the Root-Mean-Squared-Error (CV(RMSE)), the Root-Mean-Squared-Error (RMSE), and the Mean Bias Error (MBE) are used to assess the precision of the models for the different data sets - Equations (15) to (17) as defined by IPMVP (2007). A CV(RMSE) of 3-5% for prediction of power input at the component level is acceptable (Haberl and Bou-Saada 1998, Kammerud et al. 1999).

$$CV(RMSE) = \frac{\sqrt{\frac{\sum_{i=1}^{n}\left(y_{i,predicted} - y_i\right)^2}{n-1}}}{y_{mean}} \cdot 100 \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{i,predicted} - y_i\right)^2}{n-1}} \tag{16}$$

$$MBE = \frac{\sum_{i=1}^{n}\left(y_{i,predicted} - y_i\right)}{n} \tag{17}$$

where y_i is the measured value, $y_{i,predicted}$ is the predicted value, y_{mean} is the mean of the measured value sample data, and n is the number of data.

An additional criterion, the Relative Error (R.E.), is used to compare the estimates of energy consumption with the measured values over the verification set (Equation (18)).

$$R.E. = \frac{\sum_{i=1}^{n}\left(y_{i,predicted} \cdot \Delta t\right) - \sum_{i=1}^{n}\left(y_i \cdot \Delta t\right)}{\sum_{i=1}^{n}\left(y_i \cdot \Delta t\right)} \tag{18}$$

Training and testing

The estimated electric power input to the chillers provides good results over the training sets for models established using 30 hours or 28 days of data for chiller CH1, and more than 7 days of data for chiller CH2 (Table 6). Over the testing set, the CV(RMSE) does not exceed 4.5% for the CH1-30H and CH1-28D data sets. For chiller CH2, the developed models provide good results over the testing sets, with the exception of the CH2-1D data set: the CV(RMSE) does not exceed 4.2% and the average MBE does not exceed -10.8 kW.

Pre-determined coefficients are available in the EnergyPlus program. The chillers installed at the Concordia Sciences Building are Trane CVHF0910 model with COP of 5.76 at design conditions. This model is not available as a default in EnergyPlus. Therefore, the Trane chiller model that has the closest capacity, which is the Trane CVHF0796 with COP of 6.4, is used for comparison purposes. The coefficients identified for the CH1-28D and CH2-7D sets as well as the default EnergyPlus file are presented in Table 5. The coefficients identified for chiller CH1 and chiller CH2 are different, thus demonstrating the need to develop different models even if the chillers are identical. The difference in the performance characteristics of the chillers are a result of distinct operating patterns. Also, since different data sets are used to develop each model, the identified coefficients vary from one data set to another.

Figure 1 presents the measured electric power input variations compared to (1) the EnergyPlus model developed using the proposed technique for the CH1-28D and (2) the default EnergyPlus model. The prediction made by the proposed technique over part of the testing set shows agreement with the measured data, especially when the electric power input is high, while the prediction made using the default Trane coefficients available in EnergyPlus underestimates the electric power input. The CV(RMSE) over the testing set for the CH1-28D using the proposed approach is 4.5%, while being 12.3% when the Trane coefficients available in EnergyPlus are used.

Verification over the remaining summer season

For the verification set, it is assumed that the monitored data represent normal operating conditions that prevailed during the training and testing periods. The verification set is used to further assess the performance of the models for a longer period of time.

For the models where the coefficients are identified from measurements following the proposed approach, the CV(RMSE) over the testing set are lower than 7.4% (Table 6) for all training data sets, with one exception for chillers CH1 and CH2 (CH1-10D and CH2-1D). However, the CV(RMSE) over the verification set vary between 6.0-12.3% and 7.4-9.6%, respectively for chiller CH1 and CH2 (Table 7).

For chiller CH1, the use of a training set of 28-days provides good prediction accuracy over the verification set, with CV(RMSE) not exceeding 6.0% and underprediction of the energy consumption by only 0.6%.

For chiller CH2, the CV(RMSE) are below 9.6% and R.E. below ±3.7%, except for the model trained with one day of data (CH2-1D). The use of a training set size larger than seven days does not improve the prediction accuracy of the verification set. Thus, for chiller CH2, the minimum training and testing data set for the EnergyPlus model should be seven days (CH2-7D).

Table 6
Results for the electric power input for chillers following the proposed approach – training and testing sets

ITEM	TRAINING SET		TESTING SET		
	CV, %	RMSE, kW	CV, %	RMSE, kW	MBE, kW
CH1-30H	2.9	8.9	2.5	7.4	1.72
CH1-7D	5.3	16.9	5.4	12.9	-3.95
CH1-10D	5.5	16.1	12.3	29.8	-3.42
CH1-14D	8.4	23.8	7.4	22.8	-5.29
CH1-21D	6.5	18.8	7.2	24.1	-1.37
CH1-28D	3.7	11.4	4.5	14.3	6.25
CH2-1D	10.8	30.8	11.0	37.7	10.41
CH2-7D	4.9	16.4	4.0	12.9	-5.56
CH2-10D	4.8	15.8	4.2	13.9	-1.73
CH2-14D	4.2	13.9	3.9	12.1	-2.21
CH2-21D	4.0	12.9	4.0	9.0	-1.34
CH2-28D	4.1	13.2	3.5	14.5	-10.82

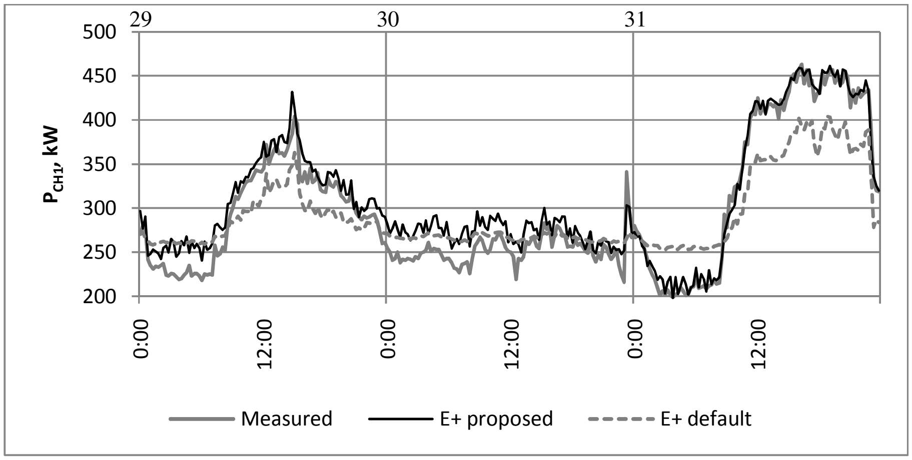

Figure 1 Chiller CH1 power electric input variation for EnergyPlus model, July 29th to July 31st 2009.

Table 7
Results for the electric power input for chillers following the proposed approach – verification set

VERIFICATION SET	CV, %	RMSE, KW	MBE, KW	R.E. ON kWh, %
CH1-30H, 07/06 to 09/22	12.3	38.5	-25.4	-9.6
CH1-7D, 07/13 to 09/22	11.7	36.9	-2.3	-2.3
CH1-10D, 07/16 to 09/22	11.9	37.7	-2.2	-2.2
CH1-14D, 07/20 to 09/22	16.0	50.9	0.2	-1.4
CH1-21D, 07/27 to 09/22	8.1	25.5	3.3	-0.5
CH1-28D, 08/03 to 09/22	6.0	18.8	3.0	-0.6
CH2-1D, 06/23 to 09/20	44.7	133.5	91.7	17.1
CH2-7D, 06/29 to 09/20	7.4	21.2	7.9	-0.7
CH2-10D, 07/02 to 09/20	8.1	22.9	10.9	-1.5
CH2-14D, 07/06 to 09/20	8.5	23.4	15.2	-0.2
CH2-21D, 07/13 to 09/20	9.4	26.2	19.2	0.3
CH2-28D, 07/20 to 09/20	9.6	26.4	20.3	3.7

Performance of the proposed approach for part-load conditions

It is important to evaluate the electric power input to the chillers at part-load conditions, particularly for this case study, since the chillers operate on average at 55-60% of their design capacity. Figure 2 presents the measured and the CH1-28D model estimates of P_E for 40-70% part-load conditions for chiller CH1. The estimated value by the proposed approach is close to the measured values for part-load conditions. Over the summer season, for the CH1-28D data sets, the CV(RMSE) is 5.3% for all part-load conditions.

Comparison with published data

Hydeman et al. (2002) have evaluated the model described by Equations (1) to (6) using manufacturer's data. For centrifugal chiller with Variable Speed Drive (VSD), the obtained CV(RMSE) were below 2.7%. Figure 3 presents the CV(RMSE) for chillers CH1-28D and CH2-7D over the training, testing, verification sets of the summer 2009 compared to the CV(RMSE) calculated by Hydeman et al. (2002). The CV(RMSE) are slightly higher than the ones available in the literature. It is worth being reminded that the proposed models use data obtained from monitoring of an existing central cooling plant, while the published data came from laboratory measurements or manufacturer data at steady-state conditions.

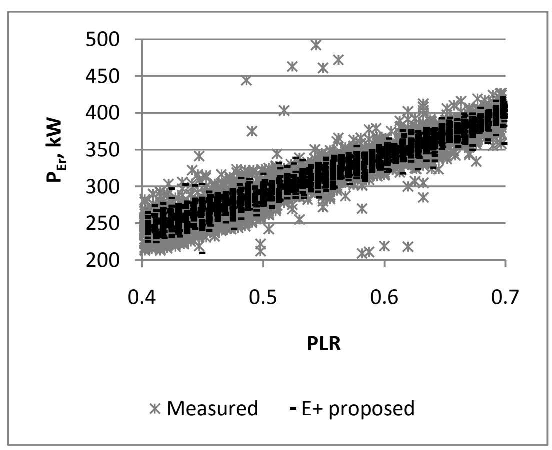

Figure 2 Measured versus estimated electric power input for CH1-28D using the proposed approach at part-load conditions for chiller CH1, based on coefficients identified using the CH1-28D data set.

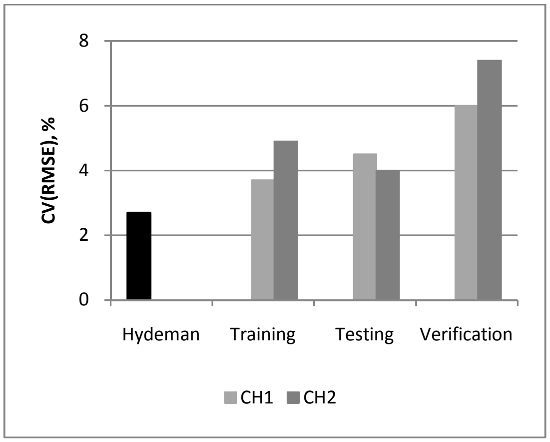

Figure 3 Comparison of the accuracy of estimates of the electric power input.

CONCLUSION

This paper proposes a modified approach to identify the coefficients of one of the models used in EnergyPlus to estimate the electric power input to chillers. The proposed approach is an extension of the Hydeman and Gillespie (2002) method, which is based on the Hydeman et al. (2002). The approach used monitored data instead of manufacturer or laboratories data to identify the coefficients of the correlations used to estimate the electric power input to chillers. Data monitored every 15 minutes were used to identify the coefficients and verify the estimated electric power input to the chillers.

Different data set sizes were evaluated and the evaluation criteria, such as the CV(RMSE), was calculated over the training, testing, verification sets for the summer 2009. The results demonstrate that 28-days of data for the first chiller and 7-days of data for the second chiller, collected at the beginning of the summer season, are sufficient to obtain accurate prediction of the electric power input to chillers. The identified coefficients using the CH1-28D and CH2-7D data sets are valid for normal operating conditions of the chillers installed in the central plant, where T_{CHWS} is ~6.8°C and the T_{CNDR} ~28°C. The CV(RMSE) for the electric power input are 3.7% and 4.9% over the training set, 4.5% and 4.0% over the testing set, and 6.0% and 7.4% over the verification set, respectively for the first and the second chillers. The energy consumption over the verification set is underestimated by less than 0.7% for both chillers.

ACKNOWLEDGEMENT

The first author acknowledges the ASHRAE Graduate Student Grant-In-Aid received for the 2009-2010 academic years and the scholarship received from the “Fonds Québécois de la recherche sur la Nature et les Technologies”. The authors would also like to thank the Faculty of Engineering and Computer Science (Concordia University) and the Intelligent Buildings Group of CanmetENERGY Research Centre (Varennes) for their support.

REFERENCES

ASHRAE.2002. Measurement of energy and demand savings. ASHRAE Guideline 14-2002.

DOE. 2009. EnergyPlus documentation. US Department of Energy.

Haberl, J.S. and T.E. Bou-Saada. 1998. Procedures for calibrating hourly simulation models to measured building energy and environmental data. Journal of Solar Energy Engineering 120:3.

Hydeman, M., and K.L. Gillespie. 2002. Tools and Techniques to Calibrate Electric Chiller Component Models. ASHRAE Transactions 108 (1): 733-741

Hydeman, M., Webb, N., Sreedharan, P., Blanc, S., 2002. Development and testing of a reformulated regression-based electric chiller model. ASHRAE Transactions 108 (2): 1118-1127.

International Performance Measurement and Verification Protocol (IPMVP). 2007. Concepts and options for determining energy and water savings 1. Efficiency valuation organization.

Kammerud, R., K. Gillespie, and M. Hydeman. 1999. Economic uncertainties in chilled water system design. ASHRAE Transactions 105(2):1075-1085.

Kreider, J.F., Haberl, J.S. Predicting hourly building energy use: The great energy shootout - overview and discussion of results. ASHRAE Transactions 1994, 100 (2): 1104-1118.

Lawrence, T. M. and J. E. Braun. 2007. Calibrated simulation for retrofit evaluation of demand-controlled ventilation in small commercial buildings. ASHRAE Transactions 113(2): 227-240.

Lebrun, J., J.-P. Bourdouxhe, and J. Grodent. 1994. HVAC 1 Toolkit: a toolkit for primary HVAC system energy calculation. ASHRAE.

Lee, S. U., F. L. Painter, and D. E. Claridge. 2007. Whole-building commercial HVAC system simulation for use in energy consumption fault detection. ASHRAE Transactions 113 (2): 52-61.

Pan, Y., Z. Huang, and G. Wu. 2007. Calibrated building energy simulation and its application in a high-rise commercial building in Shanghai . Energy and Buildings 39: 651–657.