Comparison of Chiller Models for use in Model-Based Fault Detection

Priya Sreedharan
University of California, Berkeley, and
Lawrence Berkeley National Laboratory
Berkeley, CA

Philip Haves
Lawrence Berkeley National Laboratory
Berkeley, CA

ABSTRACT

Selecting the model is an important and essential step in model based fault detection and diagnosis (FDD). Factors that are considered in evaluating a model include accuracy, training data requirements, calibration effort, generality, and computational requirements. The objective of this study was to evaluate different modeling approaches for their applicability to model based FDD of vapor compression chillers.

Three different models were studied: the Gordon and Ng Universal Chiller model (2nd generation) and a modified version of the ASHRAE Primary Toolkit model, which are both based on first principles, and the DOE-2 chiller model, as implemented in CoolTools™, which is empirical. The models were compared in terms of their ability to reproduce the observed performance of an older, centrifugal chiller operating in a commercial office building and a newer centrifugal chiller in a laboratory.

All three models displayed similar levels of accuracy. Of the first principles models, the Gordon-Ng model has the advantage of being linear in the parameters, which allows more robust parameter estimation methods to be used and facilitates estimation of the uncertainty in the parameter values. The ASHRAE Toolkit Model may have advantages when refrigerant temperature measurements are also available. The DOE-2 model can be expected to have advantages when very limited data are available to calibrate the model, as long as one of the previously identified models in the CoolTools library matches the performance of the chiller in question.

1. INTRODUCTION

Fault Detection and Diagnosis Fundamentals

The ability to detect faults in equipment can result in reduced energy and maintenance costs and extended equipment life. FDD involves two steps: detecting that a fault is present and then isolating and diagnosing it. Faults can be classified as either degradation or abrupt faults. An example of a degradation fault is the gradual leakage of refrigerant from a chiller or an air conditioning unit. Model-based FDD automates the fault detection process, reducing the need for manual inspection of performance data. Figure 1 describes the general process of model-based fault detection:

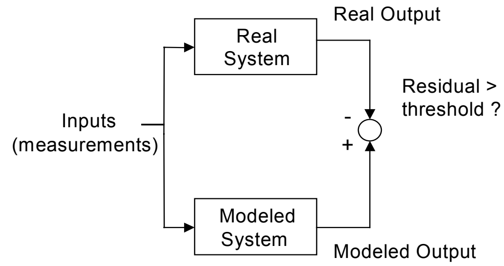

Figure 1. Fault Detection Schematic

The inputs are sensor measurements or control signals. The model processes the measured data and generates an output, which is then compared to the actual output from the system. Residuals, or 'innovations' that exceed a pre-determined threshold indicate the presence of a fault. The selection of the model is an important step that governs the accuracy of fault detection. Three models were studied to assess their applicability to model-based FDD of chillers.

Modeling Basics

Models can be classified into two broad classes: empirical (black-box), and analytical (physical or first principles).

Empirical models do not incorporate any kind of prior knowledge of the system. Examples of empirical models include polynomial curve fits, and artificial neural networks. An advantage of empirical models is that detailed physical knowledge of the system is not necessary. A disadvantage is that the model is reliable only for operating points within the range of the training data, and extrapolation outside this range may lead to significant error. In order to properly train the model, adequate training data are required; the richer the data, the more accurate the model predictions.

Analytical or *physical models*, also known as white-box models, are largely based on the laws of physics. Physical models may require less training data, since the model should be valid at all operating conditions for which the assumptions inherent in the model are valid. A disadvantage is that a good understanding of the physical phenomena is necessary for an accurate model, which is not always available. In practice, a model may be partly empirical and partly based on first principles. (Haves, 1999)

Desirable Characteristics of a Model

The selection of a model is based on a variety of criteria. These include:

- accuracy
- calibration effort and training data requirements
- computational scheme
- physical relevance of parameters (for physical models)

All but the first require some explanation. The more limited the range of conditions for which training data are required, the more quickly and easily these data can be obtained. Although computational load is not usually a problem, the estimation of the values of the parameters of a model that is both non-linear in the inputs and non-linear in the parameters can be both slow and uncertain.

When physical models are used, the parameters obtained through calibration should be physically meaningful. For example, if their values suggest the presence of a fault, not only is a fault detected, but in addition, the cause of the fault may be more easily identified.

Selected Models

The following steady-state chiller models were selected for this study:

1) ASHRAE Primary Toolkit Model (Bourdouxhe *et al.* 1997)
2) Gordon-Ng Universal Chiller Model (Ng *et al.* 1997)
3) CoolTools/ DOE-2 Model (PG&E, 2001)

The first two models were selected because they are both physical models, but differ somewhat in their formulation and structure. The Primary Toolkit model is a component-based model, whose equations are solved iteratively. The Gordon-Ng Universal model uses a systems approach and the model structure provides a simple, explicit solution. The DOE-2 model is an empirical model based on polynomial curve fits. Each model is described in subsequent sections of the paper.

All models selected are steady-state models, and cannot be applied to data obtained during transient operation. The model selection was limited by the kind of measurements and information available for the chillers studied. For example, heat exchanger dimensions were not available for the building chiller. Refrigerant temperature and pressure measurements were also unavailable for the building chiller, and are not generally available on-line, although this is slowly changing.

2. DESCRIPTION OF DATA

Laboratory Chiller

Performance data from a centrifugal, 90 ton (316 kW) water-cooled McQuay chiller installed in a laboratory at Purdue University were collected by Comstock *et al.* (2001) as part of an ASHRAE-sponsored research project. The test rig was designed to meet the American Refrigeration Institute specifications for testing chillers, with the goal of simulating the load of a real building. Water flow rates and temperatures were measured on both the condenser and evaporator sides. Temperatures were measured by Resistance Temperature Detectors (±0.05°F). Vortex flow meters were used to measure the water flow rates (±1%). The electric power consumed by the compressor motor was measured using a watt transducer (±1.5%).

An energy balance was performed, together with an uncertainty analysis using the method outlined in Figliola (1995). The uncertainty analysis indicates that the observed energy imbalance is not due to sensor uncertainty alone. Furthermore, the energy balance shows a significantly stronger correlation with the compressor power than with either the evaporator or condenser load. This suggests that the energy imbalance is associated with the motor or the compressor and could be a result of electromechanical losses from the motor to the environment. The correlation of the energy imbalance with compressor power is shown in Figure 1.

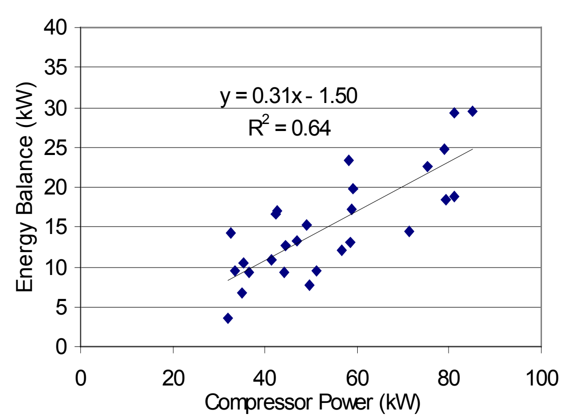

Figure 1. Energy Balance vs. Compressor Power

Two versions of the laboratory data set were used to test the physical models, the original and one in which the compressor power measurements were reduced by 30%, resulting in an approximately zero energy balance. Equally good fits were obtained with each data set, although the values of the parameters differ, as discussed below.

Building Chiller

Data was collected from an older 225 ton (791 kW) Carrier water cooled centrifugal chiller over a period of 18 months. Evaporator and condenser flow rates, temperatures, and compressor power were collected every minute using high quality sensors. Water temperatures were measured by thermistors (calibrated to ±0.008°F), water flow rates by magnetic flow meters (±0.5%) and electric power by three phase power transducers (±0.2%) (Piette, 1998).

A simple steady-state filter was developed to remove transient data. In order to produce a representative data set for calibration of the models, the entire filtered data set was binned by chilled water temperature, condenser temperature, and evaporator load. The data in each bin were averaged, and these average values comprised the training data.

An energy balance confirmed that heat losses are within 10% of the maximum compressor power and 2.5% of the evaporator load. The uncertainty in the energy balance due to uncertainty in the measurements is ±2.9 kW.

3. MODEL DESCRIPTIONS

ASHRAE Toolkit

The Toolkit model is a component-based model, the components being the evaporator, compressor, condenser, and expansion device. Sensible heat exchange is ignored in both the condenser and the evaporator, which are modeled using the effectiveness-NTU method assuming an infinite capacity rate on the refrigerant side. The electromechanical losses from the compressor are assumed to be a combination of a constant loss and a loss proportional to the compressor power. These losses are assumed to heat the refrigerant sensibly before it enters the compressor. The model assumes no energy is lost to the environment. The Toolkit includes reciprocating, screw and centrifugal compressor models; the main difference between the three is in the equations used to estimate the volumetric flow rate through the compressor. Compression at full load is assumed to be isentropic for all compressor types. Centrifugal compression is assumed to be isentropic at both full and part load. The real compressibility factor is used in modeling the refrigerant, which is otherwise treated as an ideal gas. (Bourdouxhe, 1994)

The ASHRAE Toolkit model was restructured to resembled the other models, such that the compressor power for a given chiller load is predicted. With the additional input of evaporator load, the model could be calibrated using both full-load and part-load data. Also, fewer parameters, particularly the compressor parameters used to estimate volumetric flow rate, need to be estimated. The main physical concepts, particularly, the compressor efficiency relationships, and heat exchanger models, were retained. In addition, the nested-looped computational scheme was made more efficient by replacing the 'one-point iteration' method with the secant method.

Alternative Calibration Method

The Toolkit includes a centrifugal chiller calibration routine that uses full load data, linear regression, and a simple grid-type search method. A direct search method is required because the model is non-linear in the parameters and the partial derivatives of the function are not easily evaluated. In the work reported here, the Nelder-Mead Simplex method (Nelder, 1965) was used to calibrate the model. The root mean square error of the power prediction was considered as the objective (error) function. The parameters of the model are the heat exchanger conductances (UA_e, UA_c), the fixed losses from the compressor (W_{lo}) and the fraction representing compressor losses proportional to the power (α).

Gordon-Ng Universal Chiller Model

The model is based on both energy and entropy balances, thus incorporating both the first and second laws of thermodynamics. As in the ASHRAE Toolkit model, sensible heat exchange is ignored in both the condenser and the evaporator, which are modeled using the effectiveness-NTU method assuming an infinite capacity rate on the refrigerant side. Heat losses to, and gains from, the environment are treated. The performance equation is expressed in a form that is linear in physically meaningful parameters.

$$\frac{T_{ei}}{T_{ci}}\left(1+\frac{1}{COP}\right)-1=\frac{T_{ei}}{Q_e}\Delta S_T+Q_{leak,eqv}\frac{\left(T_{ci}-T_{ei}\right)}{T_{ci}\times Q_e}+\frac{R\times Q_e}{T_{ci}}\left(1+\frac{1}{COP}\right)$$

where:

T_{ei} is the evaporator inlet water temperature,

T_{ci} is the condenser inlet water temperature,

COP is the ratio of evaporator duty (kW) to compressor power (kW), and

Q_e is the evaporator duty (kW)

The three performance parameters are:

a) total internal entropy production, ΔS_T

b) total heat exchanger 'thermal resistance',

$$R = \frac{1}{\varepsilon_c \dot{m}_c c_{pw}} + \frac{1}{\varepsilon_e \dot{m}_e c_{pw}}$$

(Note that R is not equal to the sum of the reciprocals of the conventional UA values but of UA values defined in terms of the difference between the inlet water temperature and the refrigerant temperature rather than the log mean temperature difference.)

c) equivalent heat leak ,

$$Q_{leak,eqv} = Q_{leak,e} + \frac{Q_{leak,comp} \times T_{ei}}{T_{ci} - T_{ei}},$$

where $Q_{leak,e}$ is defined as an energy gain, and $Q_{leak,comp}$ is defined as an energy loss.

The dependence of $Q_{leak,eqv}$ on the condenser and evaporator inlet temperatures has a small effect on COP for properly operating commercial chillers, according to the model's authors. While the other parameters may also have slight dependence on temperatures, the authors found that adopting constant values resulted in performance predictions whose errors are less than the effects of typical measurement errors. The model is calibrated by linear regression. Once calibrated, the equation is rearranged to solve for COP or power explicitly.

Comparison with Toolkit Model

The Toolkit and Gordon-Ng models are both physical models, but differ in their approach and assumptions. These are listed in Table 1. Note that, as mentioned earlier, the models also differ computationally, as well as in their method of calibration.

DOE-2 Model Description

The chiller model used in the DOE-2 building energy simulation program is an empirical model that predicts chiller power consumption from the evaporator outlet and condenser inlet water temperatures and the evaporator duty. The model is based on three polynomial curves:

$$CAPFT = a_1 + b_1 \times T_{eo} + c_1 \times T_{eo}^2 + d_1 \times T_{ci} + e_1 \times T_{ci}^2 + f_1 \times T_{eo} \times T_{ci}$$
$$EIRFT = a_2 + b_2 \times T_{eo} + c_2 \times T_{eo}^2 + d_2 \times T_{ci} + e_2 \times T_{ci}^2 + f_2 \times T_{eo} \times T_{ci}$$
$$EIRFPLR = a_3 + b_3 \times PLR + c_3 \times PLR^2,$$
$$where\ PLR = \frac{Q_e}{Q_{e,available(Teo,Tci)}}$$

Table 1. Comparison of Physical Model Assumptions

Toolkit	Gordon- Ng
Neglects environmental losses in the energy balance	Includes environmental losses in the energy balance
Assumes isentropic compression.	Estimates entropy generation.
Requires refrigerant thermo-physical properties	Does not require refrigerant properties.
Evaporator and condenser water flow rates are treated as variables (although the effect of flow rate on the convective heat transfer coefficient, and hence on the UA's, is ignored).	Evaporator and condenser water flow rates are treated as constants (and incorporated into the thermal resistance parameter), although there is a variable condenser flow rate version of the model. [1]
Evaporator and condenser UA's are determined separately	A single effective thermal resistance is determined for the whole chiller
Electromechanical losses are proportional to the compressor power.	Combined evaporator and compressor leaks are constant, independent of compressor power.

1 This version is non-linear in the parameters when considering variable condenser water flow rate. (Gordon, 2000)

The first curve describes how the cooling capacity of the chiller varies at different inlet water temperatures, in comparison to the cooling capacity at reference conditions, normally 44°F (6.7°C) and 85°F (29.4°C). The second curve describes how the full load (in)efficiency, defined as power consumption in kW per ton of cooling varies with inlet water temperatures and the third curve describes how the power consumption varies at part load conditions.

CoolTools is a software package developed by the Pacific Gas and Electric Company (PG&E) to facilitate calibration of the DOE-2 model. Calibration of the DOE-2 model requires full and part-load data. The model can be directly calibrated by linear regression if sufficient data are available at both full and part load. Data required are inlet evaporator and condenser water temperatures, compressor power, and evaporator load. The parameters for the capacity (CAPFT) and efficiency (EIRFT) curves are found using full-load data, while the part-load power curve (EIRPPLR) is calibrated with part-load data as well.

Chillers rarely operate at full load in the field. To facilitate the calibration of the DOE-2 chiller model from field operating data, the CoolTools project collected operating data both at full and part load from over 100 chillers and used these data to generate a library of curves that is included in the CoolTools package. When limited performance data are available, a curve that matches the data can be selected from the library, usually resulting in a significantly better model than would have been obtainable otherwise.

4. MODELING RESULTS

The modeling results are organized firstly by model type and secondly by chiller. A summary of parameter values, and r.m.s. error is included at the end of this section.

ASHRAE Toolkit Laboratory Chiller Results

Table 2 shows the parameter sets that were estimated for the ASHRAE Toolkit model from the measured performance of the laboratory chiller. The parameters of a minimum. The model was then exercised with a range of heat exchanger parameters, while holding the compressor loss parameters at their optimized values. Figure 2 shows the shape of the objective function, which follows the expected behavior, in that the heat exchanger UA's are inversely related. The sum of the reciprocals of the UA's is approximately constant, indicating that the total thermal resistance of the condenser and the evaporator is well-defined by the performance data.

Table 2. ASHRAE Toolkit Parameters: Laboratory Chiller

Parameter	Original Data	Adjusted Data
UA_e (kW/K)	92.49	68.54
UA_c (kW/K)	170.37	171.36
α (–)	0.0	0.28
W_{lo} (kW)	18.09	26.82

A comparison of the predicted and measured compressor powers is shown in Figure 3. The root mean square (r.m.s) of the absolute prediction errors is 1.95 kW and the r.m.s. of the fractional prediction errors is 3.69%. The uncertainty in model predictions due to measurement errors in the input data is estimated to be 0.83 kW or 1.37%.

ASHRAE Toolkit Building Chiller Results

Table 3 shows the parameters that were estimated for the ASHRAE Toolkit model from the measured performance of the building chiller. Again,

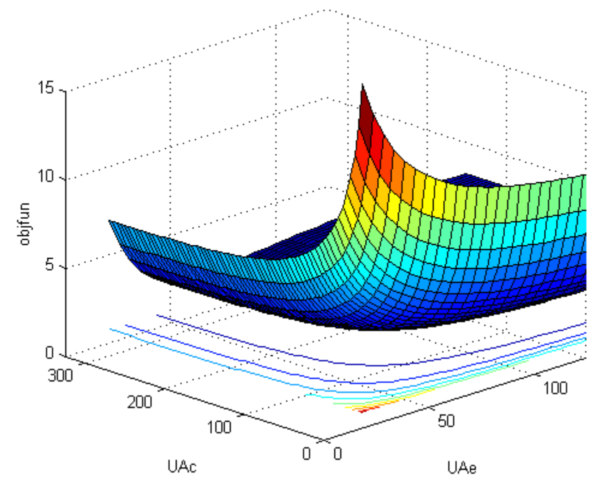

Figure 2. Objective function – Laboratory Chiller

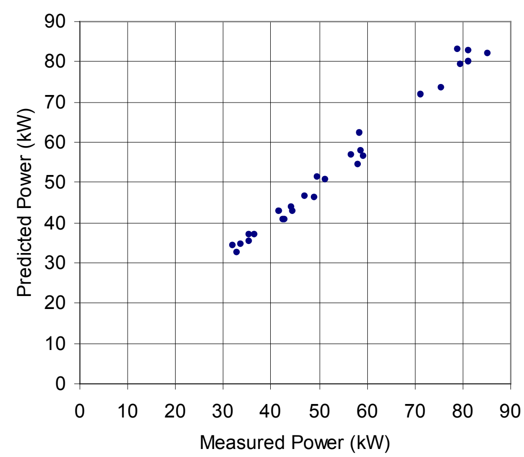

Figure 3. Toolkit Model Results –Laboratory Chiller

the model parameters were perturbed to confirm a minimum, and the model was exercised with a range of heat exchanger UA's, while holding the loss terms at their optimized values. The shape of the objective function, shown in Figure 4, is similar to that of the lab chiller. Surprisingly, the UA's are larger for the laboratory chiller, although the building chiller has a larger capacity (by more than a factor of two).

Table 3. ASHRAE Toolkit Parameters: Building Chiller

Parameter	Value
UA_e (kW/K)	54.54
UA_c (kW/K)	135.98
α (–)	0.00
W_{lo} (kW)	41.40

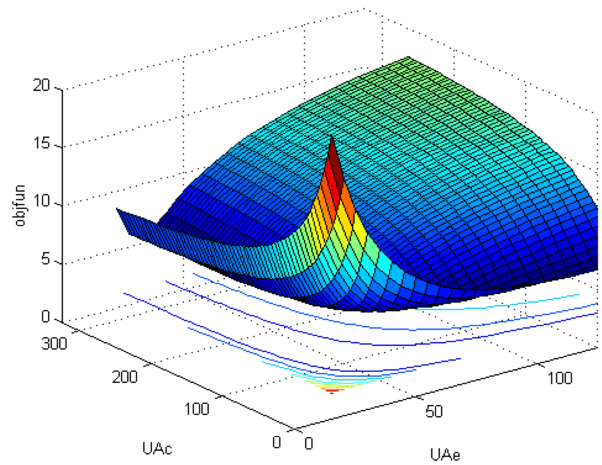

Figure 4. Objective Function – Building Chiller

A comparison of the predicted and measured compressor powers is shown in Figure 5. The significant discontinuity at 105 kW is found in the results from the other models as well. The high power points are distinguished by larger differences between the condenser and evaporator water temperatures, as shown in Figure 6. However, the expected decrease in efficiency resulting from the higher pressure lift is not observed, either in this chiller or in the other, similar, chiller in the building. In addition, the condenser water flows, as well as the evaporator water flows, were verified to be constant, which is a prerequisite for using these particular models.

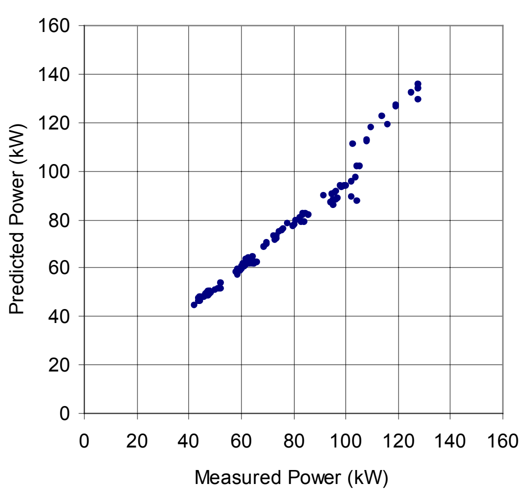

Figure 5. Toolkit Model Results – Building Chiller

The r.m.s. absolute error is 4.09 kW and the relative error is 4.82%. The corresponding uncertainties in the model predictions due to measurement errors

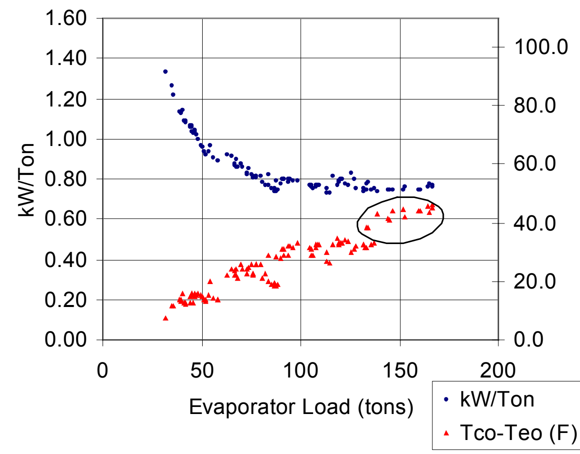

Figure 6. Efficiency and Temperature Lift

in the input data are 0.32 kW and 0.34%. This uncertainty is particularly small, and is even less than the uncertainty in the flow measurement, because it is biased towards measurements of low power. In the low power regime, a reduction (or increase) in flow, and hence, load, results in a comparatively small decrease (or increase) in power since the efficiency deteriorates rapidly.

<u>Gordon-Ng Laboratory Chiller Results</u>

Table 4 shows the parameter sets that were estimated from the measured performance of the laboratory chiller.

Table 4. Gordon-Ng Parameter Sets: Laboratory Chiller

Parameter	Original Data	Adjusted Data
ΔS_T (kW/K)	0.080	0.058
R (K/kW)	0.079	0.051
$Q_{leak,eqv}$ (kW)	105.65	35.26

<u>Comparison with Toolkit Model</u>

As expected, the heat leak term, $Q_{leak,eqv,}$ is significantly larger for the original data. However, considering the maximum compressor power is 85 kW, the original data set heat leak term seems unreasonably high. Ng (1997) determined heat leaks on the order of 40% of the maximum compressor power for two reciprocating chillers. The large heat leak estimate may be an outcome of the model's assumption of constant heat leaks over the operating range. This assumption is not valid for the original data, which show that compressor losses are strongly dependent on compressor power. For the adjusted data, the constant heat loss term from the Toolkit model, $W_{lo,}$ is larger than the heat leak term in the

Gordon-Ng model. This may be explained by the assumption of isentropic compression in the Toolkit model, which is an idealization that must be 'corrected' with a larger compressor loss term. The unusually large equivalent heat leak obtained from the original data cannot be explained in this way.

A comparison of the predicted and measured compressor powers is shown in Figure 7. These results showed trends similar to the Toolkit results. The r.m.s. absolute error is 2.21 kW and the relative error is 3.73%. The corresponding uncertainties in the model predictions due to measurement errors in the input data are 0.68 kW and 1.09%.

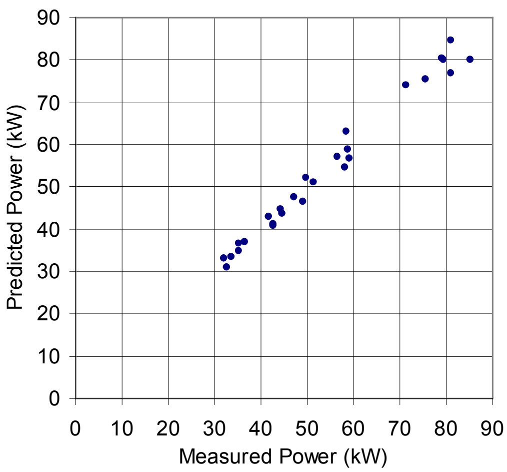

Figure 7. Gordon-Ng Model Results: Laboratory Chiller

Gordon-Ng Building Chiller Results

Table 5 shows the parameter estimates for the building chiller.

Table 5. Gordon-Ng Parameters: Building Chiller

Parameter	Value
ΔS_T (kW/K)	0.134
R (K/kW)	0.043
$Q_{leak,eqv}$ (kW)	12.05

Parameter Comparison with Toolkit

The entropy generation for the building chiller was larger than for the lab chiller by 100% for the adjusted data, and 50% for the original data. The value for the adjusted data is what would be expected for a machine of approximately twice the capacity.

The estimate of the heat loss parameter is 12 kW, which was approximately 7% of the maximum compressor power (180 kW). This value is low compared to the 40% obtained by Ng et. al (1997) and the even larger fraction found for the laboratory chiller. (Unlike the laboratory chiller, the building chiller did not exhibit significant heat losses to the environment, as indicated by the heat balance.) The equivalent heat loss term can be compared to the compressor loss term obtained in the Toolkit model. Again, the compressor losses from the Toolkit model were larger than the heat leak estimate from the Gordon-Ng model, which may be due to the assumption of isentropic compression in the Toolkit model; an idealization that must be 'corrected' with a larger compressor loss term.

Table 6 shows the thermal resistance values estimated for the two models and the two chillers. The heat exchanger parameters from the Toolkit model were used to calculate the equivalent thermal resistance as defined in the Gordon-Ng model. They are less than the resistances estimated for the Gordon-Ng model, particularly for the original data, but as in the results for the Gordon-Ng model, the thermal resistance estimated from the original data using the Toolkit model is larger than that estimated from the adjusted data.

Table 6. Thermal Resistance of Physical Models

Thermal Resistance (K/kW)	Toolkit	Gordon-Ng
Lab Chiller – Original Data	0.040	0.079
Lab Chiller – Adjusted Data	0.037	0.051
Building Chiller	0.034	0.043

As shown in Table 6, the heat exchanger parameters for the building chiller estimated using the Toolkit model are equivalent to a thermal resistance of 0.034 K/kW, somewhat less than the 0.043 K/kW obtained from the Gordon-Ng model., but these results are closer than the results for the lab chiller. For both the lab and building chillers, the thermal resistances obtained from the two models are significantly different, although the ranking is the same in each case. That is, the thermal resistance for the building is less than that of the lab chiller using adjusted data, which in turn is less than the thermal resistance for the lab chiller using the original data.

A comparison of the predicted and measured compressor powers is shown in Figure 8. The results are similar to those for the Toolkit and show large residuals for the same data. In particular, the discontinuity at ~105 kW is similar to that seen in the Toolkit results. The r.m.s. absolute error is 4.01 kW and the relative error is 3.86%. The corresponding uncertainties in the model predictions due to measurement errors in the input data are 0.37 kW and 0.40%.

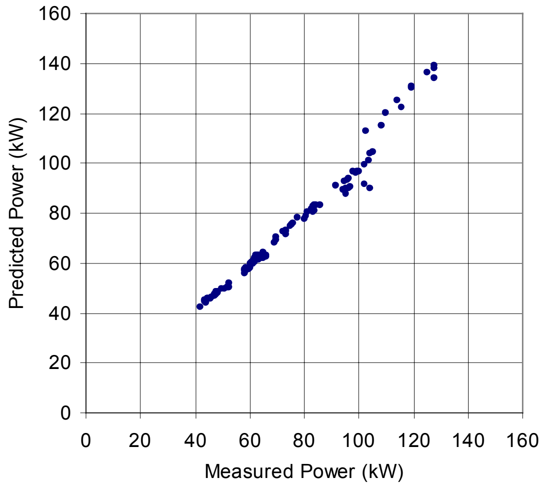

Figure 8. Gordon-Ng Model Results – Building Chiller

DOE-2 Laboratory Chiller Results

Figure 11 shows the DOE-2 results for the laboratory chiller, obtained by direction calibration. Compared to the physical models, the DOE-2 model shows a better fit at high duty and a poorer fit at low duty. This is a consequence of the calibration method, which utilizes full-load and part-load data separately. The r.m.s. absolute error is 2.42 kW and the relative error is 5.26%. The corresponding uncertainties in the model predictions due to measurement errors in the input data are 0.58 kW and 0.99%.

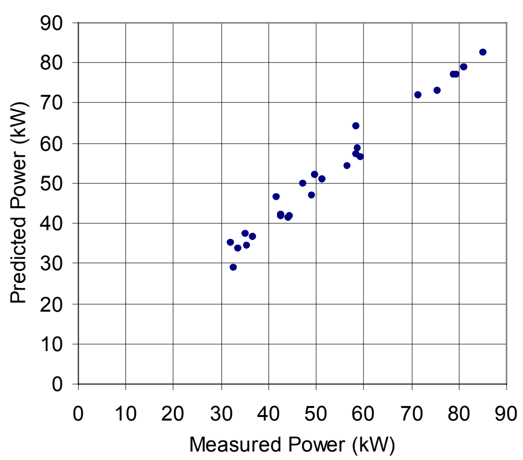

Figure 11. DOE-2 Model Results - Laboratory Chiller

DOE-2 Building Chiller Results

Since full load data for the building chiller were unavailable, the CoolTools software was used to select a chiller curves that have already been fitted to the DOE-2 model. Each parameter set in the library is tested using data from the chiller to be calibrated and the curve producing the lowest RMSE is selected.

Figure 9 shows a comparison of the measured power and the power predicted by the selected CoolTools library curve. The results closely resemble the results from the other models.

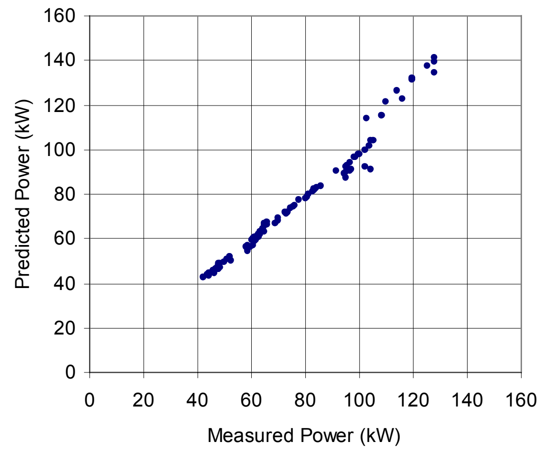

Figure 9. CoolTools Model Results – Building Chiller

The r.m.s. absolute error is 4.24 kW and the relative error is 4.03%. The corresponding uncertainties in the model predictions due to measurement errors in the input data are 0.37 kW and 0.41%.

Table 6 summarizes the results from this section.

Table 6. Summary of Modeling Results

	Laboratory Chiller		Building Chiller
	Original Data	Adjusted Data	
r.m.s.e. – TK (kW)	1.95	1.34	4.09
r.m.s.e. – G-Ng (kW)	2.21	1.38	4.01
r.m.s.e. – DOE-2 (kW)	2.42	1.92	4.24
W_{lo} – TK (kW)	18.09	26.82	41.40
α – TK (––)	0.00	0.28	0.00
UA_e – TK (kW/K)	92.49	68.54	54.54
UA_c – TK (kW/K)	170.37	171.36	135.98
R – TK (K/kW)	0.040	0.037	0.034
R – G-Ng (K/kW)	0.079	0.051	0.043
ΔS_T (kW/K)	0.080	0.058	0.134
Q_{leak} (kW)	105.65	35.26	12.05

5. DISCUSSION

The ability of the models to reproduce the observed behavior, as indicated by the r.m.s. prediction errors, is quite similar. The similarity of the graphs of predicted vs. measured power indicates that the dominant sources of error are either in the measurements or result from behavior that none of the models treat. The variation in the parameter values from model to model and chiller to chiller can be explained in terms of the assumptions of the models.

- The isentropic compression assumption in the Toolkit model results in a larger estimate for the loss term, as compared to the Gordon-Ng model, which accounts for entropy generation in compression.
- The Gordon-Ng model's assumption of constant heat losses/gains over the operating range results in unreasonably large estimates of the leak parameter, questioning the ability of this model to treat chillers with heat losses proportional to compressor power.
- The Toolkit model, as used in this study, produced larger estimates of the heat exchanger coefficients (UA's) for the laboratory chiller, although the building chiller had a significantly larger cooling capacity. The estimates of thermal resistance, as defined in the Gordon-Ng model, were larger for the laboratory chiller, though not as large as would be expected from the difference in the cooling capacities of the two chillers.

A significant discontinuity in the relationship between predicted and measured power was observed with all three models. The chiller appears to perform more efficiently than expected at higher loads, assuming that the difference between the condenser and evaporator water temperatures is a reasonable proxy for pressure lift. Discussion with one of the CoolTools developers confirmed that this behavior is not observed in the data in the CoolTools library (Hydeman, 2001).

6. CONCLUSIONS

All three models displayed similar levels of accuracy. Of the first principles models, the Gordon-Ng model has the advantage of being linear in the parameters, which allows more robust parameter estimation methods to be used and facilitates estimation of the uncertainty in the parameter values. The ASHRAE Toolkit Model may have advantages when refrigerant temperature measurements are also available, since it should be possible to predict the expected performance of the compressor, condenser and evaporator separately with more confidence than has been found to be possible with only water side thermal measurements. The DOE-2 model can be expected to have advantages when very limited data are available to calibrate the model, as long as one of the previously identified models in the CoolTools library matches the performance of the chiller in question.

ACKNOWLEDGEMENTS

Thanks are due to James Braun of Purdue University for providing the performance data for the laboratory chiller. This work was supported by the California Energy Commission and by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technology, State and Community Programs of the U.S. Department of Energy under Contract No. DE-AC03-76SF00098.

REFERENCES

Bourdouxhe, J. P., M. Grodent and J. J. Lebrun. 1994. "A Toolkit for Primary HVAC System Energy Calculation – Part 2: Reciprocating Chiller Models", ASHRAE Transactions, vol. 100, Part 2, pp. 774-786.

Bourdouxhe, J. P., M. Grodent and J. J. Lebrun. 1997. "HVAC1 Toolkit: Algorithms and Subroutines for Primary HVAC System Energy Calculations", The American Society of Heating, Refrigerating and Air Conditioning Engineers.

Braun, J. 1999. "Automated Fault Detection and Diagnostics for the HVAC&R Industry", International Journal of Heating, Ventilating, Air-Conditioning and Refrigerating Research, vol. 5, no.2, pp. 85-86.

Comstock, M. and J. E. Braun, 1999. "Development of Analysis Tools for the Evaluation of Fault Detection and Diagnostics in Chillers", Ray W. Herrick Laboratories Report #4036-3.

Comstock, M., J. E. Braun and E.A. Groll, 2001. "The Sensitivity of Chiller Performance to Common Faults", In Press, International Journal of Heating, Ventilating, Air-Conditioning and Refrigerating Research.

Figliola, R., S. and D. E. Beasley. 1995. Theory and design for mechanical measurements (Second Edition). John Wiley & Sons, Inc., NY.

Gordon, J. M., K. C. Ng, H. T. Chua and C. K. Lim. 2000. "How varying condenser coolant flow rate affects chiller performance: thermodynamic modeling and experimental confirmation", Applied Thermal Engineering, vol. 20, pp. 1149-1159.

Gordon, J. and K. C. Ng. 2000. Cool Thermodynamics. Cambridge International Science Publishing. UK.

Haves, P. and S. Khalsa. 2000. "Model-based Performance Monitoring: Review of Diagnostic Methods and Chiller Case Study", Proc. ACEEE Summer School, Asilomar, CA, August, LBNL Report 45949

Haves, P. 1999. "Overview of Diagnostics Methods", Proceedings of Diagnostics for Commercial Buildings: From Research to Practice, San Francisco, CA. http:/poet.lbl.gov/diagworkshop/proceedings/haves.htm

Hydeman, M. 2001. Personal Communication.

Isermann, R. and P. Balle. 1997. "Trends in the application of model-based fault detection and diagnosis of technical processes", Control Engineering Practice, vol.5, no.5, pp. 709-719.

Nelder, J. A. and R. Mead. 1965. "A Simplex method for function minimization", The Computer Journal, vol. 8, pp. 308-313.

Ng, K. C., H. T. Chua, W. Ong, S. S. Lee and J. M. Gordon. 1997. "Diagnostics and optimization of reciprocating chillers: theory and experiment", Applied Thermal Engineering, vol. 17, no. 3, pp. 263-276.

Pacific Gas and Electric, 2001. “CoolTools: a Toolkit to Optimize Chilled Water Plants”, San Francisco, CA. http://www.hvacexchange.com/cooltools/

Piette, M. A., S. Khalsa, P. Rumsey, K. L. Kinney, E. L. Lee, A. Sebald, and C. Shockman. 1998. "Early Results and Field Tests of an Information Monitoring and Diagnostic System for Commercial Buildings", prepared for the California Energy Commission and the California Institute for Energy Efficiency, LBNL 42338, September. Downloadable from http://poet.lbl.gov/imds/phase2/

Schwefel, H. P. 1995. Evolution and Optimum Seeking. John Wiley & Sons, Inc., NY.