Reevaluation of the Gordon-Ng Performance Models for Water-Cooled Chillers

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ABSTRACT

Selecting a performance model is an important and essential first step in improving the operation of existing chiller systems. Of the several chiller models proposed in the literature, one promising approach is the physical model formulation proposed by Gordon and Ng (GN). It has been evaluated by a couple of previous studies and found to be less accurate in predictive ability than black-box chiller models such as that used by DOE-2. The findings of these studies can be faulted on the grounds that an older and more restrictive version of the GN chiller model (called quasi-empirical model) was used. The objective of this study is to perform a thorough evaluation of the internal and external predictive ability of the GN class of models and several of their variants so that any lingering uncertainty can be dispelled. Over 50 chiller data sets from all of the major chiller manufacturers have been used in this study. Chiller types studied include single- and double-stage centrifugal chillers with inlet guide vane and variable-speed drive capacity control, screw, scroll, and reciprocating chillers, as well as two-stage absorption chillers. It was found that the fundamental GN formulation for all types of vapor compression chillers is excellent in terms of its predictive ability, yielding CV values in the range of 2% and 5%, comparable to the experimental uncertainty of many chiller performance data sets.

Further, the model coefficients in the GN models have a clear physical interpretation, i.e, these coefficients can be linked to thermal characteristics specific to the chiller components. Another objective of this study was to determine whether one could detect patterns among the model coefficients across different types and sizes of screw and centrifugal chillers (single- and double-stage inlet guide vane controlled chillers and variable-speed drive chillers) and provide physically consistent explanations for these patterns. These trends may be useful to chiller manufacturers since this would provide a simple and direct means to evaluate a particular prototype chiller under development as against broad industry trends and specific competitor's chiller models. These trends specific to chiller type and size may also be useful to general HVAC&R practitioners in understanding the relative importance of the various sources of irreversibilities to which the chiller industry has optimized their designs due to technical and economic considerations.

INTRODUCTION

Engineering models for HVAC&R equipment and systems are, broadly speaking, meant for two types of applications:

1. *Simulation models* used for either improving equipment performance (focus of equipment manufacturers and CAD designers) or for system optimization during the design phase, i.e., selecting the most appropriate set of equipment and its control (focus of design consultants).
2. *Performance models* used to improve the operation of existing equipment and systems (focus of maintenance and service personnel), which includes such activities as: certified and witnessed factory testing, start-up commissioning, periodic commissioning, automated fault detection and diagnosis (FDD), supervisory control, sequencing, and optimization.

The primary focus of this study is toward (2) above as applied to chillers and chiller plants. In the last few years, there has been a resurgence of interest in chilled water plant design (Taylor et al. 1999; Taylor 2001), procurement (Corcoran and

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Reddy 2003), FDD (Sreedharan and Haves 2001), commissioning and diagnosis (Hydeman et al. 1999; Reddy et al. 2001), and supervisory control (Braun 1988). A crucial element is the ability to accurately model the thermal behavior of various types of chillers—both vapor compression and absorption types—based on performance data collected under a wide range of operating conditions. Note that the term "modeling" implies two processes: selection of a model form, and then estimating the model parameters from the specific data at hand.

The choice of a particular model among competing models is based on the following considerations: (1) model prediction accuracy, (2) training data requirements (number of sensor points and length), (3) effort needed to calibrate or train the model, (4) generality of the model, (5) computational requirements, and (6) the ability to physically interpret the model coefficients, i.e, their physical relevance (Sreedharan and Haves 2001). A few years back, Gordon and Ng (GN) proposed a new modeling approach to chiller behavior (Gordon and Ng 1994) that has been expanded in several papers by Gordon, Ng, and collaborators and is summarized in the book by Gordon and Ng (2000). While a few studies have shown that the various chiller models are comparable in their predictive ability (see, for example, Reddy and Anderson [2002]; Sreedharan and Haves [2001]), the GN model offers clear superiority in terms of the other attributes, as testified in papers by Phelan et al. (1997), Gordon and Ng (2000), Reddy and Anderson (2002), Anderson and Reddy (2002), Corcoran and Reddy (2003), and Reddy et al. (2001).

However, a recent performance model evaluation study by Hydeman and Gillespie (2002) concluded that the GN models were less accurate in terms of their predictive ability than other model formulations under certain cases, such as variable-speed drives, noncentrifugal compressors, and air-cooled condensers. This is inconsistent with the findings of Gordon and Ng (2000), who performed extensive accuracy tests using performance data from numerous small-sized cooling capacity chillers. More specifically, GN models have been evaluated by the authors with (1) 30 data points from a 10.5 kW water-cooled reciprocating chiller in the laboratory (CV < 2.2%), (2) 60 data points from a 70.4 kW water-cooled reciprocating chiller in the field (CV < 5%), (3) 12 reciprocating air-to-air chillers (which included variable airflow [CV <5%], (4) 7 absorption chillers (which included single, double, and triple stage chillers), and (5) over 30 reciprocating water-cooled chillers. Further, Reddy et al. (2001) also found the GN model to be excellent for two large field-operated centrifugal chillers. Part of the confusion and uncertainty has been due to there being two generations of vapor compression models (called quasi-empirical and fundamental), along with a couple of model variants specific to chiller design and operating alternatives (say, variable condenser flow rate operation or variable-speed drive control as against inlet guide vane control for centrifugal chillers), as well as statistical reasons associated with the chiller data set on which the evaluations were performed. The study by Hydeman and Gillespie (2002), as well as that by Phelan et al. (1997), used the quasi-empirical GN model formulation and not the superior fundamental chiller model. Hence, a careful reappraisal of the GN models and their range of application to large water-cooled chillers is warranted so that these models can be accepted by the professional community and used routinely with confidence by service and maintenance personnel.

OBJECTIVE

The major objective of this paper is to perform a detailed reevaluation of the prediction accuracy of various GN models (to be used for field operation as against chiller simulation purposes) using performance data from 51 chillers from different manufacturers. The data sets used are, in large part, a subset of the ones used by Hydeman and Gillespie (2002) and Hydeman et al. (2002). Chiller types studied include centrifugal chillers with inlet guide vane and variable-speed drives, screw, scroll, and reciprocating chillers, as well as absorption chillers. Since there is a clear physical interpretation of the model coefficients in the GN models, i.e, these coefficients can be linked to thermal characteristics specific to the chiller components, another objective of this study is to determine whether one can detect patterns among the coefficients across different chillers of the same type. This would provide insight on how the various chiller manufacturers have empirically optimized the various components in chillers.

CHILLER MODELING

Instead of distinguishing modeling approaches according to application area (as described previously), one can also do so based on the type of data presumed known or specified.

1. *Detailed mechanistic approach* (also called "forward modeling"), where one starts with a detailed knowledge of the physical geometry and construction of each of the subcomponents of the system and develops a set of system equations based on mass, momentum, and energy balances, along with heat and mass transfer correlations. It is a good approach for chiller design since it can allow a designer to simulate the detailed behavior of the complete system and thereby evaluate design alternatives in the physical manner in which subcomponents are built and in the way the whole chiller is operated. This approach has been used to model steady-state chiller behavior (for example, Braun 1988; Browne and Bansal 1998; MacIntosh 1999), as well as transient behavior (for example, Browne and Bansal 2002; Koury et al. 2001; Willatetzen et al. 1998).
2. *Inverse or data-driven models* (also called "in-situ modeling" by a few researchers) applicable to existing chillers where the model is identified, usually by least-squares regression, from monitored performance data. Again, the models can be steady-state or transient, though the former are the most widely used. This modeling approach is advantageous for proper control, commissioning, and fault detec-

tion. Inverse models can be subdivided into: (a) *gray box models* if the model has scientific underpinnings, such as being based on the laws of physics and engineering understanding of the working of the system (usually lumped or simplified mechanistic formulations are adopted due to statistical limitations in identifying the model parameters), and (b) *black box models* if based on empirical and statistical considerations (for example, when one fits empirical relationships to either performance data or manufacturer's data, such as described by Stoecker [1989]).

The black box model approach (also called "empirical model approach") is relatively easy to implement since detailed understanding of the working of the system is not necessary. The limitation of this method is that the model can only be trusted within the range of conditions for which it was fit, allows no fault diagnosis capability, and is unsuitable for analyzing design improvements. Often the available data are too limited to provide a complete performance map. ANN models (for example, Bailey 1998; Bechtler et al. 2001; Reddy et al. 2001; Swider et al. 2001) can also be considered to fall into this category.

Whereas the structure of a gray box model, such as the GN model, is determined from the underlying physics, the black box model is characterized as having no (or sparse) information about the physical problem incorporated in the model structure, and a statistical or empirical relationship between input and output is formulated. Using the same parameters as those for the physical model, previous research studies (for example, Braun [1988]) have adopted a second-order linear polynomial model (termed *multivariate polynomial model* by Reddy and Andersen [2002]) with three regressor variables (usually condenser inlet water temperature, chiller inlet [or outlet] water temperature, and the thermal load on the chiller). The above model has ten coefficients that need to be identified from monitored data. These coefficients, unlike the three coefficients appearing in the GN model, have no physical meaning, and their magnitude cannot be interpreted in physical terms. Usually one needs to retain in the model only those parameters that are statistically significant, and this is done by step-wise regression (Chatterjee and Price 1981). A detailed description of the model identification process is given in Reddy and Andersen (2002). A simpler black box chiller model formulation is presented by Kreider et al. (2002), which relies on knowing the rated chiller COP, the rated chiller capacity, and three empirical coefficients that form a linear second-order model with part-load ratio (PLR) as the regressor variables.

Hydeman and Gillespie (2002) and Hydeman et al. (2002) adopted different versions of the black box multivariate polynomial chiller model based on the algorithm used in the commercially available DOE-2 simulation program (Winklemann et al. 1993). It consists of determining three models: (1) the available capacity as a function of evaporator and condenser temperatures, (2) the full-load efficiency as a function of evaporator and condenser temperatures, and (3) efficiency as a function of percentage loading. In total, there are 15 model parameters that need to be identified from data. The authors recommend that 20 to 30 data points be used for model identification, covering the entire range of operating conditions. A limitation in using this approach is that full-load and part-load data have to be separated during model fitting, an unwieldy procedure when dealing with in-situ performance data. It should be noted that this type of chiller model was originally developed for the purpose of simulating quasi-steady-state performance to be used for building and associated HVAC&R equipment design. In this respect, it has the ability to predict chiller thermal capacity under different conditions of chiller and condenser inlet water temperatures. The GN model, on the other hand (as well as most of the models discussed above), is meant for performance prediction (either the chiller COP or the electric power consumed), with the chiller thermal load and the two operating temperatures being explicitly known or specified.

Physical models generally have fewer model parameters than black box models and also require less training data. There are, essentially, two physical (or gray box) chiller model formulations proposed in the literature: the toolkit models developed by Bourdouxhe et al. (1996) as part of an ASHRAE research project, which consist of a set of computational tools based on physical algorithms for primary HVAC equipment. These are closer to lumped inverse component models (such as effectiveness-NTU models for condenser and evaporator and electromechanical losses from the compressor), but the estimation of the parameters is nonlinear and calibration to readily available data is difficult (Sreedharan and Haves 2001; Hydeman et al. 2002). On the other hand, the GN models are the easiest to calibrate to field-measured data and do not require explicit separation of full-load and part-load data. Further, the GN models described below only need as few as four well-chosen data points for accurate model identification (Corcoran and Reddy 2003).

DESCRIPTION OF THE GN MODELS

Fundamental Model for Vapor Compression Chillers with Constant Flow

This is a simple, analytical, universal (i.e., applies to all chiller types) model for chiller performance based on first principles of thermodynamics and linearized heat losses. The model predicts the dependent chiller COP (defined as the ratio of chiller or evaporator thermal cooling capacity Q_{ch} by the electrical power P consumed by the compressor) with specially chosen independent and easily measurable parameters such as the fluid (water or air) inlet temperature from the condenser T_{cdi}, fluid temperature entering the evaporator (or the chilled water return temperature from the building) T_{chi}, and the thermal cooling capacity of the evaporator. The fundamental model is a three-parameter model, which, for parameter identification, takes the following form:

$$\left(\frac{1}{COP}+1\right)\frac{T_{chi}}{T_{cdi}}-1$$
$$= a_1\frac{T_{chi}}{Q_{ch}}+a_2\frac{(T_{cdi}-T_{chi})}{T_{cdi}Q_{ch}}+a_3\frac{(1/COP+1)Q_{ch}}{T_{cdi}} \quad (1)$$

where the temperatures are in absolute units, and the parameters of the model have physical meaning in terms of irreversibilities.

$a_1 = \Delta S$ = the total internal entropy production rate in the chiller due to internal irreversibilities

$a_2 = Q_{leak}$ = the rate of heat losses (or gains) from (or into) the chiller

$a_3 = R = \dfrac{1}{(mCE)_{cond}} + \dfrac{1-E_{evap}}{(mCE)_{evap}}$, i.e., the total heat exchanger thermal resistance, which represents the irreversibility due to finite-rate heat exchange.

The model applies to both unitary and large chillers operating under steady-state conditions. Further, the assumptions during model development indicate that this model is strictly applicable to inlet guide vane capacity control (as against cylinder unloading for reciprocating chillers, or VSD for centrifugal chillers).

Manufacturer catalog data are often reported in terms of the chilled water supply temperature to the building (T_{cho}) instead of T_{chi}. In that case, Equation 1 remains unaltered when T_{chi} is replaced by T_{cho}, though the physical interpretation of the coefficient a_3 is modified a little (Gordon and Ng 2000). In this study, we have used T_{cho} in all our analyses.

If we introduce

$$x_1 = \frac{T_{cho}}{Q_{ch}},\ x_2 = \frac{T_{cdi}-T_{cho}}{T_{cdi}Q_{ch}},$$
$$x_3 = \frac{(1/COP+1)Q_{ch}}{T_{cdi}},\ \text{and } y = \left(\frac{1}{COP}+1\right)\frac{T_{cho}}{T_{cdi}}-1\ ,$$

the *fundamental chiller model*, given by Equation 1, with T_{chi} replaced by T_{cho}, becomes

$$y = a_1x_1 + a_2x_2 + a_3x_3\ , \quad (2)$$

where the three model parameters a_1, a_2, and a_3 can be determined by regressing performance data.

Hence, the reformulation provides a model that is linear in the parameters but without an intercept term. As discussed by Gordon and Ng (2000), one should not include the intercept term if the model parameters are to be interpreted in terms of physical quantities since Equation 2 has been derived from fundamental laws of thermodynamics and heat transfer. However, if the model is to be used purely for predictive purposes, the inclusion of an intercept in this model may better account for the inaccuracies that appear in in-situ data containing instrument errors (as suggested by some data analysis texts, for example, Schenk [1968]). Hence, in order to dispel any doubt, we shall also evaluate the following variant of Equation 2, which though nonphysical, may provide better model prediction accuracy.

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 \quad (3)$$

Capacity control by inlet guide vanes is most common in large centrifugal chillers. However, variable-speed drive control devices are being increasingly adopted. Here, the rotational speed of the compressor, and, hence, refrigerant flow rate, is reduced to modulate the chiller. Modern chiller controls are a bit more complex, since they rely on sensors internal to the chiller (Hydeman et al. 2002). These controls are set to preferentially operate the VSD for efficiency and rely on the compressor inlet vanes to keep the chiller out of "surge" conditions. Gordon and Ng (2000) point out that for centrifugal chillers with inlet guide vane control, the rate of entropy production due to internal dissipation is roughly independent of cooling rate because of compensation between specific rate of entropy production and flow rate. This may or may not apply to centrifugal chillers with variable-speed drive. Since it is likely that the refrigerant flow rate may change the internal entropy production in the compressor, we propose to evaluate a slight variant to the original fundamental model (albeit in an empirical fashion) by assuming the rate of entropy production to be linear in the variable (Q_{ch} / $Q_{ch,max}$). Consequently, Equation 1 with T_{chi} replaced by T_{cho} modifies to

$$\left(\frac{1}{COP}+1\right)\frac{T_{cho}}{T_{cdi}}-1 = \left(b_1+b_2\frac{Q_{ch}}{Q_{ch(max)}}\right)\frac{T_{cho}}{Q_{ch}} + b_3\frac{(T_{cdi}-T_{cho})}{T_{cdi}Q_{ch}}+b_4\frac{(1/COP+1)Q_{ch}}{T_{cdi}}\ . \quad (4)$$

If we introduce

$$x_1 = \frac{T_{cho}}{Q_{ch}},\ x_2 = \frac{T_{cho}}{Q_{ch(max)}},\ x_3 = \frac{T_{cdi}-T_{cho}}{Q_{ch}T_{cdi}},$$
$$x_4 = \frac{(1/COP+1)Q_{ch}}{T_{cdi}},\ \text{and } y = \left(\frac{1}{COP}+1\right)\frac{T_{cho}}{T_{cdi}}-1\ ,$$

our empirical modification to the fundamental chiller model for *variable-speed drive chillers* assumes the following form (which is a four-parameter model):

$$y = b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \quad (5)$$

If an intercept term were to be included due to statistical reasons stated earlier, the corresponding model would assume the following form:

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \quad (6)$$

Fundamental Model for Vapor Compression Chillers with Variable Condenser Flow

Although to date, most commercial chillers are designed and installed to operate at constant coolant flow rates, variable condenser water flow operation (as well as evaporator flow rate) is being increasingly used. In order to accurately correlate chiller model performance under variable condenser flow, Gordon and Ng developed an analytic model as follows:

$$\frac{T_{cho}(1+1/COP)}{T_{cdi}} - 1 - \frac{1}{(V\rho C)_{cond}}\frac{(1/COP+1)Q_{ch}}{T_{cdi}} = c_1\frac{T_{cho}}{Q_{ch}} + c_2\left(\frac{T_{cdi}-T_{cho}}{Q_{ch}T_{cdi}}\right) + c_3\frac{Q_{ch}(1+1/COP)}{T_{cdi}} \tag{7}$$

If we introduce

$$x_1 = \frac{T_{cho}}{Q_{ch}},\ x_2 = \frac{T_{cdi}-T_{cho}}{Q_{ch}T_{cdi}},\ x_3 = \frac{(1/COP+1)Q_{ch}}{T_{cdi}}, \text{ and}$$
$$y = \frac{T_{cho}(1/COP+1)}{T_{cdi}} - 1 - \frac{1}{(V\rho C)_{cond}}\frac{(1/COP+1)Q_{ch}}{T_{cdi}},$$

Equation 7 for the *variable condenser flow rate* assumes the form,

$$y = c_1x_1 + c_2x_2 + c_3x_3, \tag{8}$$

while the model with an intercept term will be

$$y = c_0 + c_1x_1 + c_2x_2 + c_3x_3. \tag{9}$$

Quasi-Empirical Model with Constant Flow

Like the fundamental model, the empirical model is also a simple three-parameter formula. It can predict COP using the same parameters (T_{cdi}, T_{cho}, and Q_{ch}) as the fundamental model. But the difference is that each of the parameters cannot be assigned a single clear physical significance as in the fundamental model. The quasi-empirical model takes the following form:

$$\left(\frac{1}{COP} + 1 - \frac{T_{cdi}}{T_{cho}}\right)Q_{ch} = d_0 + d_1T_{cdi} + d_2\frac{T_{cdi}}{T_{cho}} \tag{10}$$

If we introduce

$$x_1 = T_{cdi},\ x_2 = \frac{T_{cdi}}{T_{cho}}, \text{ and } y = \left(\frac{1}{COP} + 1 - \frac{T_{cdi}}{T_{cho}}\right)Q_{ch},$$

the *quasi-empirical model for vapor compression systems*, given by Equation 10, becomes

$$y = d_0 + d_1x_1 + d_2x_2. \tag{11}$$

The quasi-empirical model was originally developed for reciprocating chillers (Gordon and Ng 1994). Further, it is strictly valid only when cooling rate is essentially varied by changing coolant temperatures (and not by off-loading cylinders). This would effectively limit part-load operation of reciprocating chillers to about 70% of full load. This model was verified for 30 reciprocating chillers in the range of 30 to 1300 kW of rated capacity. Gordon and Ng (2000) found that the quasi-empirical model was also appropriate for centrifugal chillers under a narrow range of operating conditions.

Quasi-Empirical Thermodynamic Model for Absorption Chillers

ARI Standard 560 (ARI 1986) applies to absorption chillers. Absorption chillers have the same type of irreversibility in the condenser and evaporator as mechanical chillers. However, the quasi-empirical thermodynamic model was modified with the consideration of the losses at the generator and absorber. The approximate formula for absorption chillers is (Gordon and Ng 2000)

$$\left(\frac{T_{geni}-T_{cdi}}{T_{geni}COP} - \frac{T_{geni}-T_{cho}}{T_{cho}}\right)Q_{ch} = e_0 + e_1\frac{T_{cdi}}{T_{geni}}. \tag{12}$$

This model is a two-parameter model; e_1 and e_2 characterize the irreversibilities of a particular chiller.
If we introduce

$$x_1 = \frac{T_{cdi}}{T_{geni}} \text{ and } y = \left(\frac{T_{geni}-T_{cdi}}{T_{geni}COP} - \frac{T_{geni}-T_{cho}}{T_{cho}}\right)Q_{ch},$$

the *quasi-empirical model for absorption chillers* given by Equation 12 becomes

$$y = e_0 + e_1x_1. \tag{13}$$

The above model is strictly applicable to single-stage chillers since the approximation of a roughly constant rate of internal dissipation still holds. How well this model applies to double-stage (or triple-stage) chillers is an issue worth investigating (and which was done in this study).

DESCRIPTION OF CHILLER DATA SETS

Hydeman and Gillespie (2002) point out that with the advent of ARI standards (ARI 1986, 1998), chiller manufacturers discontinued the publication of extensive performance data for their various chillers. Performance data for most electric chillers are available only through the manufacturer sales representatives using proprietary software (versions of which change over time).[1] Though this software is ARI-certified, chiller manufacturers have tended to adopt the practice of presenting data under "derated" conditions where the ARI-allowed measurement tolerances are used to overstate the chiller capacity and COP (Taylor 2001). Different manufacturers use different derating values (the usual range is 3% to 5%). Since the data sets supplied to us contained data from different manufacturers during different years (ranging from 1992 till 1998), we were careful to use the most recent data, which were stated to be *zero-tolerance data*.

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1. Gordon and Ng (2000) point out that some chiller manufacturers tend to simply interpolate performance data from a relatively few (five to six data points) well-chosen data points for publication in catalogs or to supply it to those requesting such data. Significant discrepancies between model and such "interpolated data" were found in such cases, which disappear when "real data" were used instead. Chiller analysts should make note of this aspect; otherwise, erroneous conclusions can be reached.

In this study, we have analyzed the following data sets:

a. Data for 46 vapor compression chillers (Taylor et al. 1999) that are generated from chiller manufacturer ARI-certified proprietary software. Some of the data sets apply to two-stage chillers as well.

b. Data for three steam-fired two-stage absorption chillers from published catalogs of a large chiller company.

c. Data for two hot water two-stage field-operated absorption chillers from a large cogeneration facility.

The 46 data sets represent centrifugal, screw, reciprocating, and scroll compressors from all of the major chiller manufacturers. All chillers have full-load and part-load conditions. Centrifugal chillers data both with and without variable-speed drives are included. All chillers were water cooled with constant flow rate except one centrifugal chiller that had variable condenser flow rate with inlet guide vane control. Each data set had 19~52 measurements of T_{chi}, T_{cdi}, Q_{ch}, and P. The data sets also gave the information of refrigerant, unloading mechanism, and chiller code for different kinds of chillers (see Appendix B). The data sets for the two field data sets of absorption chillers, both of which were two-stage hot water units, have 20 sets of measurements of T_{chi}, T_{cdi}, T_{geni}, Q_{ch}, and Q_{gen} under field-operated conditions. Each of the data sets for the three chillers under (b) above were obtained from published catalogs for steam-fired absorption chillers and contained 183 sets of measurements of T_{chi}, T_{cdi}, Q_{ch}, m_{steam}, and Pr_{gen}.

Rated cooling capacity used in this study is chiller cooling capacity under standard rating conditions specified in ARI Standard 550/590 (ARI 1998). Most of the rated cooling capacities given in Appendix B are actually close approximations because we could not get chiller cooling capacity and operating temperatures under the exact same rating conditions as stipulated by the standard. So we selected the cooling capacity under conditions closest to the standard rating conditions. Appendix B provides pertinent details for 51 chiller data sets used in this study.

We have generated scatter plots of Q_{ch} and COP vs. T_{cdi} and T_{cho} for several chillers (not shown in the paper) as part of our exploratory data analysis. These plots provide clear insight into the design of the simulation runs needed to generate the chiller performance data. Basically, they were done with T_{cdi} kept constant at five different temperature levels and varying T_{cho} at five different levels. Overall, the data sets for the vapor compression chillers covered a wide and full range of likely operating conditions, a general prerequisite for identifying sound models.

DATA ANALYSIS RESULTS

Internal Predictive Ability

Typical values of measurement uncertainty in carefully performed laboratory tests are on the order of 1% to 2% CV, while those of field performance data are about 3% to 5% (Hydeman et al. 2002; Corcoran and Reddy 2003). These provide a means of evaluating how good the regression models are compared to instrumentation uncertainty tolerances. Also, there is some ambiguity as to whether the data are zero-tolerance or derated, although we were careful in selecting zero-tolerance data to the best of our knowledge.

The intent of this part of the study was to evaluate how accurately the various Gordon-Ng models can fit actual chiller performance data. The standard least-squares linear regression method is adopted to identify the model coefficients directly from data for all 51 chiller data sets. How well the models fit the data can be ascertained from two statistical measures: R^2 and CV. Two different definitions of CV have been used, as discussed in Appendix A.

As an illustration, Figure 1 presents the model residuals on COP for one centrifugal inlet guide vane chiller against COP itself and each of the three important variables (as described in standard textbooks, for example, Chatterjee and Price [1981]). The 2σ and 3σ bands (where σ is the model RMSE) are also shown since they are often used as limiting bands for fault detection purposes. Though distinct residual patterns can be detected, the residuals are well bounded by these bands. Similar types of residual patterns were found for VSD chillers using either Equation 2 or Equation 5 and are not shown in this paper. The reevaluation results are summarized in Tables 1 through 6. We note the following:

1. The quasi-empirical model is poor for all vapor compression chillers, indicating that the quasi-empirical model (as pointed out by Gordon and Ng [2000]) cannot predict COP correctly for nonreciprocating chillers, especially when operated under a wide operating range. On the other hand, the fundamental model is excellent, with high R^2 (>90%) and low CV (in the range 2-5%). Hence, the results indicate that the fundamental model can be used with confidence for commercial centrifugal chillers, as well as screw, reciprocating, and scroll machines.

2. Model fits for the quasi-empirical model for two-stage absorption chillers are not very good (CV about 5% to 8%). This was to some extent to be expected since this model, as stated earlier, was developed for single-stage absorption machines. However, the model may still be acceptable given that these were data from catalogs and field-operated chillers where data quality assurance was poorer than the data sets (a) (see Table 6).

3. Looking at the CV values, we conclude that results of the model fits based on the fundamental model with intercept are slightly better than those without intercept. Nonetheless, it can be argued that the GN fundamental model without intercept should be the model of choice since it is still very accurate while providing the added benefit of yielding physically meaningful coefficients.

4. For a centrifugal chiller with variable-speed drive, we had proposed a modification to the fundamental model by introducing an additional parameter (see Equation 5). Inspection of Table 2 reveals that the regression results for the modified

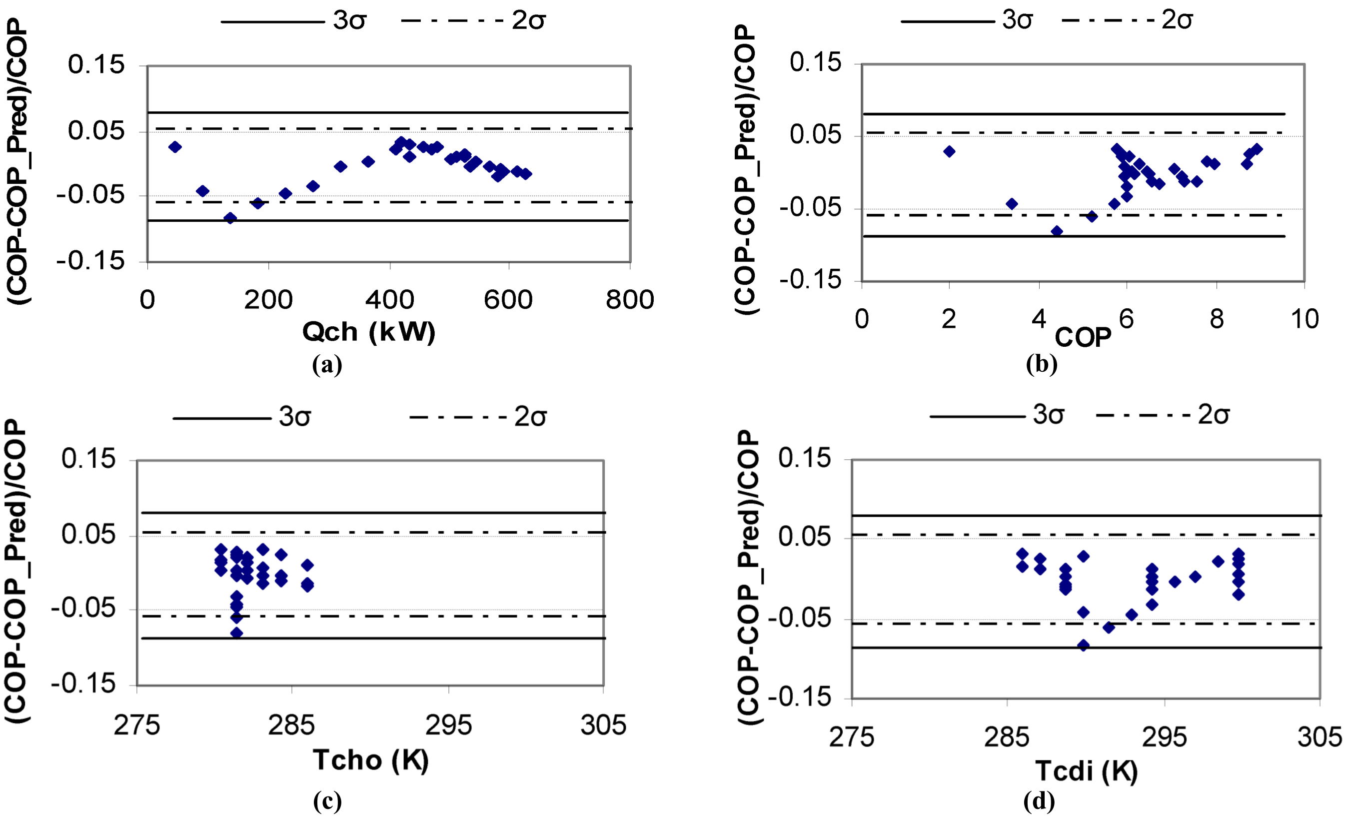


Figure 1 *Residuals in chiller COP using the GN fundamental model (chiller #397—centrifugal inlet guide vane). Also shown are the two and three standard deviation bands.*

TABLE 1
Centrifugal Chillers with Inlet Guide Vane Control (CV and R^2 are in %)

Chiller ID	Empirical Model (Equation 11)			Fundamental Model with Intercept (Equation 3)			Fundamental Model without Intercept (Equation 2)		
	R^2	CV	CV^*	R^2	CV	CV^*	R^2	CV	CV^*
400	18.4	30.1	31.5	92.3	7.3	7.5	91.8	7.3	7.5
397	25.5	22.9	24.7	99.6	3.6	3.1	99.4	2.5	2.9
380	59.5	19.6	19.4	88.1	2.8	2.5	85.6	3.2	2.9
354	2.6	15.4	17.4	99.4	1.9	1.8	99.1	2.1	2.1
370	55.0	13.3	17.0	99.7	2.9	2.7	99.0	4.6	4.6
395	42.0	20.1	23.8	99.8	3.9	3.2	99.7	4.3	3.7
372	69.1	17.8	16.3	95.4	1.9	1.6	90.7	2.5	2.2
369	33.5	35.9	33.2	96.7	3.0	3.0	96.2	3.2	3.1
375	69.8	13.8	16.3	99.9	1.0	1.0	99.9	1.6	1.5
394	22.2	18.4	21.9	98.3	3.3	3.0	96.4	4.1	4.0
391	13.8	20.2	22.9	97.5	3.3	3.2	95.6	3.9	3.9
402	41.8	40.4	36.3	91.8	3.7	3.8	91.7	3.6	3.7
363	58.0	12.0	13.2	94.9	4.3	3.9	94.7	4.1	3.8
384	60.7	21.6	23.5	98.5	2.6	2.5	98.3	2.8	2.6
362	59.4	12.9	14.9	97.8	2.4	2.2	94.3	3.2	3.2
386	50.9	25.8	27.6	96.3	3.3	3.2	93.5	5.0	4.7

Note: The CV values apply to the chiller COP and not to the response variable *y* of the model used

TABLE 2
Centrifugal Chillers with Variable-Speed Drive (CV and R^2 are in %)

Chiller ID	Empirical Model (Equation 11)			Fundamental Model with Intercept (Equations 3 and 6)			Fundamental Model without Intercept (Equations 2 and 5)		
	R^2	CV	CV^*	R^2	CV	CV^*	R^2	CV	CV^*
371	58.0	13.8	13.0	87.4/91.6	1.5/1.3	1.5/1.3	76.2/88.2	2.2/1.5	2.0/1.4
346	10.6	59.0	38.4	90.5/97.2	4.8/3.2	5.0/2.9	89.3/90.7	6.9/4.9	5.6/4.9
378	25.8	32.9	28.9	88.7/95.6	3.4/2.2	3.2/ 2.0	85.4/89.4	3.8/3.3	3.6/3.1
392	11.1	38.7	35.4	89.5/96.5	5.2/3.3	4.8/3.0	88.7/89.9	5.3/5.1	4.8/4.7
350	29.1	32.8	28.8	95.8/97.9	2.9/2.3	2.8/2.1	95.5/95.9	3.1/2.8	2.9/2.7
357	7.1	46.2	35.9	95.4/97.6	4.5/4.3	4.1/3.4	95.4/95.5	4.5/4.4	4.0/4.0
377	24.1	38.2	32.2	92.5/97.8	3.6/2.5	3.6/2.2	90.7/93.0	4.3/3.6	4.1/3.5
376	67.8	28.2	25.9	94.1/94.3	2.2/2.2	2.1/2.1	91.5/94.0	3.1/2.2	2.8/2.1
393	17.3	41.7	36.0	94.1/97.5	4.5/ 3.5	4.1/3.0	93.5/94.4	4.5/4.4	4.2/4.1
390	14.2	36.0	33.8	95.6/98.9	3.1/1.6	3.1/1.6	92.0/96.3	4.3/2.8	4.1/2.8
379	25.0	38.5	31.9	93.0/98.1	3.9/2.8	3.9/2.4	91.4/93.4	4.6/3.9	4.3/3.8
360	34.9	33.8	29.2	92.4/95.9	6.9/5.8	4.6/3.7	79.6/93.0	10.8/6.7	7.1/4.4
364	33.6	36.9	32.3	82.6/92.1	5.4/4.0	5.3/3.9	82.1/82.5	5.6/5.5	5.4/5.4
361	57.2	12.2	13.2	94.9/97.5	4.1/2.7	3.6/2.5	93.9/95.1	4.1/4.0	3.7/3.5

Note: The CV values apply to the chiller COP and not to the response variable *y* of the model used

TABLE 3
Variable Evaporator Flow Rate Centrifugal Chiller # 358 (CV and R^2 are in %)

Chiller ID	Rated Cap (ton)	Data Points	Empirical Model (Equation 11)			Fundamental Model with Intercept (Equation 9)			Fundamental Model without Intercept (Equation 8)		
			R^2	CV	CV^*	R^2	CV	CV^*	R^2	CV	CV^*
358	375	52	22.1	14.9	16.0	86.9	3.7	3.7	93.7	3.2	3.2

Note: The CV values apply to the chiller COP and not to the response variable y of the model used

TABLE 4
Screw Chillers (CV and R^2 are in %)

Chiller ID	Empirical Model (Equation 11)			Fundamental Model with Intercept (Equation 3)			Fundamental Model without Intercept (Equation 2)		
	R^2	CV	CV^*	R^2	CV	CV^*	R^2	CV	CV^*
381	45.9	19.2	19.2	87.0	1.9	1.9	86.2	1.9	1.9
387	46.5	19.9	19.8	96.4	1.2	1.2	88.9	2.0	2.0
382	47.5	18.1	18.3	88.1	1.6	1.6	88.0	1.6	1.5
349	8.9	13.9	15.7	96.7	2.5	2.5	96.3	2.8	2.8
352	43.0	17.7	18.5	94.3	2.6	2.4	91.9	3.4	3.0
344	64.1	19.8	18.8	99.7	1.9	1.9	96.9	5.4	5.1
368	51.1	9.9	11.6	98.5	2.2	2.1	96.7	2.8	2.9
355	46.2	17.1	17.8	93.2	2.5	2.4	92.3	2.7	2.6
373	88.2	7.7	7.9	84.7	3.4	3.3	84.6	3.3	3.2
353	9.3	15.5	17.7	93.1	3.1	3.3	90.6	3.8	4.1
374	84.7	8.2	8.4	85.4	3.6	3.4	84.7	3.5	3.4
348	52.6	14.5	15.6	98.4	1.5	1.5	96.7	2.1	2.2

Note: The CV values apply to the chiller COP and not to the response variable *y* of the model used

TABLE 5
Reciprocating and Scroll Chillers (CV and R^2 are in %)

Chiller ID	Empirical Model (Equation 11)			Fundamental Model with Intercept (Equation 3)			Fundamental Model without Intercept (Equation 2)		
	R^2	CV	CV^*	R^2	CV	CV^*	R^2	CV	CV^*
290	8.5	19.2	17.5	85.9	1.1	1.1	50.3	2.3	2.1
315	2.9	25.7	23.4	98.9	0.9	0.8	96.1	1.8	1.6
316	49.9	25.5	20.8	98.8	0.7	0.7	98.5	0.8	0.8

Note: The CV values apply to the chiller COP and not to the response variable y of the model used

model yield slightly lower CV values while predicting COP, but the difference is small.

5. Table 3 reveals that the modified model (Equation 8) for the variable condenser water flow rate condition is very accurate (CV = 3.2%).
6. Finally, we find that the differences in model fits based on either CV or CV* are generally negligible, except for a few cases (for example, chillers #346 and 360). This provides an indirect testimony of the suitability of the GN model over the entire range of variability of chiller operation (see Appendix A for discussion of CV and CV* statistics).

External Predictive Ability

The results discussed in the previous section indicate that the model accurately fits the data on which it was trained. This, however, is but the preliminary step (a necessary but not sufficient criterion) in evaluating the predictive ability of a model (this type of evaluation is referred to as “internal predictive ability”). Note that some in the HVAC&R community also refer to this as “simulation error.” A model with high internal predictive ability may not necessarily be robust enough to guarantee accurate predictions under different sets of operating conditions. This is a major issue in black box models, especially ANN, but less so in physical models (Reddy and Andersen 2002). The well-accepted approach to evaluate the “external predictive ability” of such models is to use a portion of the available data set for model identification (or model training) whose predictive accuracy is then evaluated on the remainder of the data set. We have selected 12 chillers from our database and for each used two-thirds of the data for model training and the remainder for model evaluation. The results are summarized in Table 7. It is clear that the CV values of both internal and external predictions are very close, thus indicating that the GN model is robust with sound and reliable predictive ability.

Patterns in the GN Fundamental Model Coefficients

The results discussed in the previous section revealed that the fundamental model without intercept (Equation 2) is most appropriate for all vapor compression chiller types analyzed. From a physical point of view, coefficients a_1 and a_3 should always be positive, whereas a_2 can be either positive or negative depending on whether heat is gained or lost from the

TABLE 6
Two-Stage Absorption Chillers (CV and R^2 are in %)

Chiller ID	Empirical Model (Equation 13)		
	R^2	CV	CV^*
1	95.7	8.9	8.9
2	95.6	4.6	4.8
Y1	82.6	7.1	7.1
Y2	82.6	7.1	7.1
Y3	81.5	7.4	7.4

Note: The CV values apply to the chiller COP and not to the response variable y of the model used

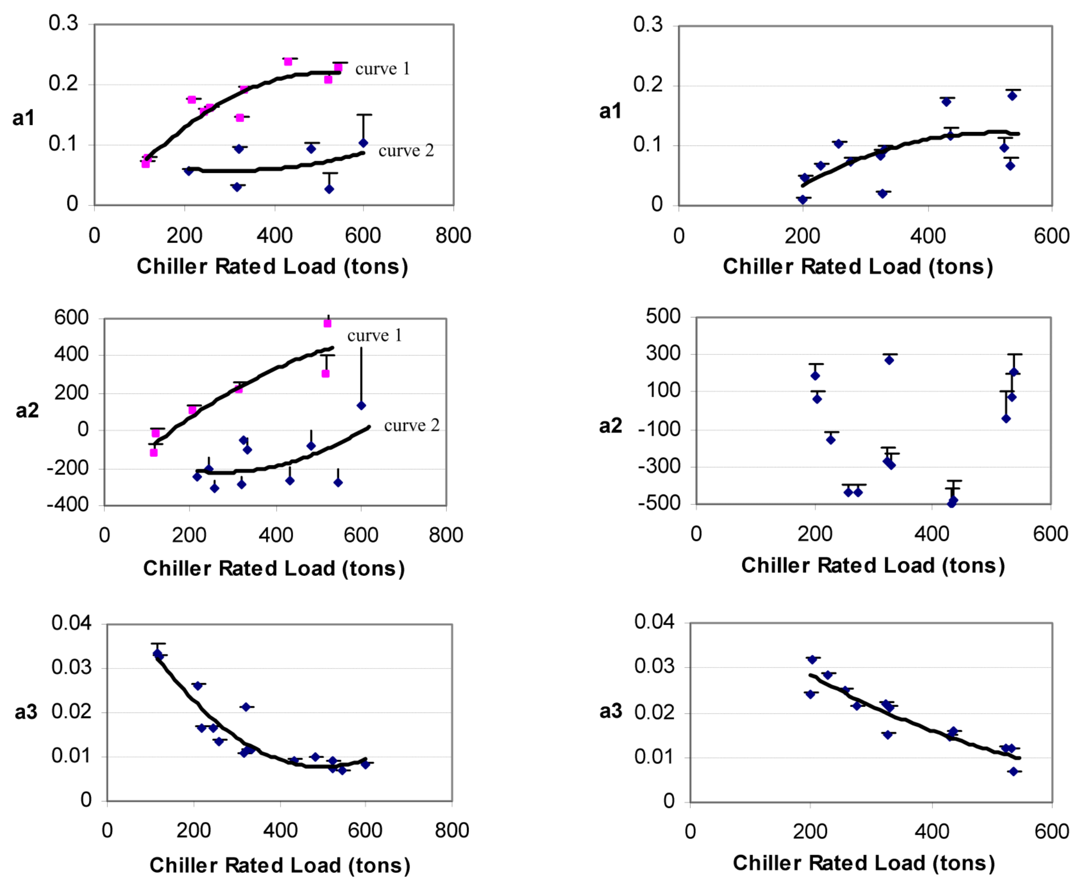
chiller. Our results verify this premise. Plots of model coefficients vs. ARI-rated load are shown in Figures 2 and 3 for centrifugal and screw chillers. It must be pointed out that determination of the ARI-rated full load could not be accurately made for some chillers since the data set provided did not contain operating conditions that exactly matched the ARI test conditions. Under such circumstances, we selected a value that was closest to the ARI test conditions. This fact is likely to have introduced some of the spread in the scatter plots. The unit of the coefficient a_1, which represents the irreversibility due to internal dissipation, is kW/K, that for a_2 is kW, and that for a_3 (which is the irreversibility due to finite heat exchange) is in K/kW.

1. We note a strong pattern in the numerical values of coefficient a_3 for all chiller types—a decreasing asymptotic trend as the rated cooling capacity of the chiller increases (a trend line is shown in the scatter plots to aid the reader). What does this imply physically? Recall that coefficient a_3 represents effective thermal resistance normalized by the cooling load for the combination of heat exchangers in chillers (Gordon and Ng 2000). This trend seems to indicate that chiller manufacturers, in an effort to improve chiller efficiency by targeting the source of external irreversibility, find it expedient to reduce the load-normalized, combined heat exchanger resistance only up to a certain chiller size. For screw chillers, the asymptote is around 300 tons, for inlet guide vane centrifugal chillers about 500 tons, and still higher for VSD chillers. These limits are probably dictated

TABLE 7
Comparison of Internal Model Prediction vs. External Prediction for Selected Chillers*

	Chiller ID	Internal Prediction		External Prediction
		R^2	CV	CV
Centrifugal with Inlet Guide Vanes (Equation 2)	397	99.4	2.5	2.7
	354	99.1	2.1	2.1
	375	99.9	1.6	1.3
	362	94.3	3.2	4.3
Centrifugal with Variable Speed Drive (Equations 2 and 5)	371	76.2/88.2	2.2/1.5	2.2/1.5
	346	89.3/90.7	6.9/4.9	6.1/3.5
	357	95.4/95.5	4.5/4.4	6.7/6.9
	364	82.1/82.5	5.6/5.5	6.1/6.5
Screw (Equation 2)	382	88.0	1.6	1.9
	352	91.9	3.4	3.7
	353	90.6	3.8	2.4
	368	96.7	2.8	3.3

* (Two-thirds of the data were used to identify the GN fundamental model, which was then used to predict the remainder. CV values apply to chiller COP).



(a) Centrifugal Chiller with Inlet Guide Vane Control

(b) Centrifugal Chiller with Variable-Speed Drive

Figure 2 *Scatter plot of regression coefficients (a_1, a_2, a_3) for centrifugal chillers vs. chiller rated capacity using the GN fundamental model (Equation 2). Standard error bars for individual points are shown along with trend lines for data scatter, which exhibit clear trends.*

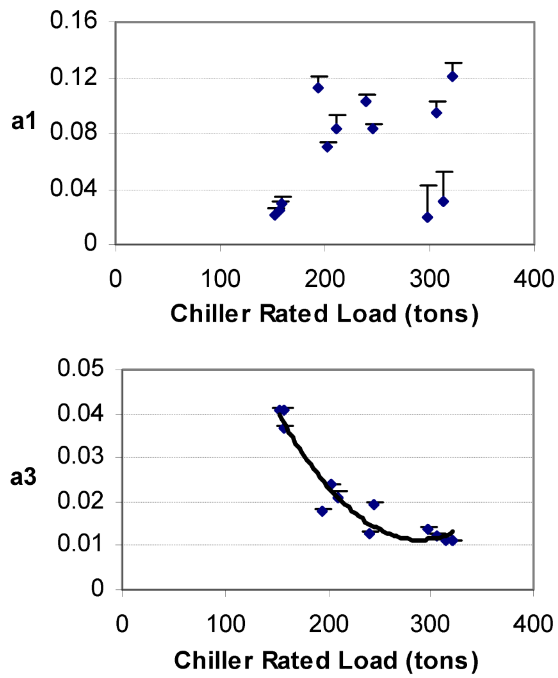


Figure 3 *Scatter plot of regression coefficients (a_1 and a_3) for screw chillers vs. chiller-rated capacity using the GN fundamental model (Equation 2). Standard error bars for individual points are shown along with trend lines for data scatter, which exhibit clear trends.*

by economics since heat exchanger performance (such as effectiveness, for example) follows the law of diminishing returns with increasing heat exchanger size or area.

2. Clearly, there is no underlying pattern in the scatter of the numerical values of the coefficient a_2. The two trend lines shown in Figure 2a correspond to single-stage and double-stage compressors, with the latter denoted by curve 2. This is not surprising since this coefficient represents the heat loss (or heat gain) from the chiller, which is affected by refrigerant type (which dictates working temperatures), as well as practical constraints such as the amount of insulation, piping length, etc.

3. The patterns of the model coefficients did not exhibit stronger trends when the four-parameter VSD model (Equation 5) was used as compared to the original three-parameter GN model (Equation 2). Hence, the parameters of the latter model have only been plotted in the first frame of Figure 2a. The numerical values of the coefficient a_1 represent the internal entropy generation due in large part to irreversibilities in the compression process. In this regard, VSD is bound to be more efficient than inlet guide vane control with single-stage compression, while two-stage compression ought to be more efficient still. Such a pattern is clearly seen from Figures 2a and 2b. Trend lines, though approximate, are shown for convenience to the reader. Curve 1 in Figure 2a corresponds to single-stage inlet guide vane chillers, while curve 2 corresponds to two-stage chillers. The plot in Figure 2b corresponds to VSD chillers and seems to fall in between the other two curves. As a note of caution, these trends need to be more comprehensively verified with future research and should be viewed as preliminary. Note that the linear positive trend indicates that large chillers have higher per unit internal dissipation losses (due to friction losses in the compressor, piping, etc.).

4. Finally, something can be said about the statistical uncertainty of the regression coefficients. This uncertainty is represented by the standard error bars, as shown in Figures 2 and 3. We note that the standard errors for the coefficients a_1 and a_3 are very small (almost indiscernible in the figures), while those of a_2 are much larger. This indicates that the coefficient a_2 is poorly identified, an observation consistent with that of Gordon and Ng (2000).

SUMMARY

The fundamental model for vapor compression chillers formulated by Gordon and Ng (2000) has been reevaluated with data supplied by various chiller manufacturers for 46 chillers. The chillers, which were water-cooled, included single-stage and double-stage centrifugal chillers (both with inlet guide vane and VSD capacity control), screw, scroll, and reciprocating chillers. It was found that the fundamental model as originally formulated without an intercept term (Equation 2) gave excellent model fits to all of the above types of chillers, with CV values in the range of 3% to 5%, which is what one could realistically expect from such data. This study also concluded that the quasi-empirical model, which was evaluated by other studies (such as Phelan et al. 1997; Hydeman et al. 2002) against the DOE-2 model and was found wanting, is generally poorer than the fundamental model formulation. Hence, it is concluded that the quasi-empirical model should only be used under the conditions for which it was originally developed: reciprocating chillers without cylinder off-loading and for centrifugal chillers operating under a narrow range of coolant and load conditions. This study also verified the suitability of the fundamental model variant proposed by Gordon and Ng for variable condenser flow (Equation 8).

Further, it was found that model fits for the quasi-empirical model for two-stage absorption chillers are poorer than for vapor compression machines (CV about 5% to 8%). This was to some extent to be expected since this model, as stated earlier, was developed for single-stage absorption machines. However, the model may still be acceptable given that these data were from catalogs and field-operated chillers where data quality assurance was poorer than for the data sets (a) (see Table 6).

Finally, this study also looked at detecting patterns among the model coefficients across different types of chillers (single- and double-stage inlet guide vane controlled chillers and variable-speed drive chillers) and provided physically consistent explanations for these patterns. These trends may be useful to chiller manufacturers since this would provide a simple and direct means to evaluate a particular prototype chiller under development as against broad industry trends and specific competitor's chiller models. These trends specific to chiller type and size may also be useful to general HVAC&R practitioners in understanding the relative importance of the various sources of irreversibilities to which the chiller industry has optimized their designs from technical and economic considerations.

ACKNOWLEDGMENTS

The authors greatly appreciate the invaluable support provided by Mark Hydeman of Taylor Engineering, LLC, Alameda. He provided us with an extensive database of chiller data sets, along with explanations of these data, and subsequent comments on this work. Robert Dewecheter of Trigen Energy Corporation provided us with measured data from two field-operated absorption chillers for which we are grateful. Finally, the insightful comments and clarifications provided by Profs. J.M. Gordon and K.C. Ng are gratefully acknowledged, as are the detailed comments by one of the anonymous reviewers.

NOMENCLATURE

C	=	specific heat, kJ/kg·K
COP	=	chiller coefficient of performance
CV, CV^*	=	coefficient of variation of the root mean square error, defined by Equations A2 and A3
E	=	heat exchanger effectiveness
m	=	mass flow rate, kg/s
n	=	number of data points
P	=	power input to the compressor, kW
Pr	=	pressure, Pa
p	=	number of model parameters
Q_{ch}	=	chiller (or evaporator) cooling capacity, kW
R	=	effective thermal resistance for the combination of heat exchangers in chillers, K/kW
R^2	=	coefficient of determination, %
RMSE	=	root mean square error, defined by Equation A1
T	=	temperature, K
V	=	volumetric flow rate, m^3/s
x	=	regressor variable
y	=	response variable
a, b, c, d, e	=	model coefficients
ρ	=	density, kg/m^3
σ	=	standard deviation or RMSE

Subscripts

cdi	=	water inlet to condenser
chi	=	water inlet to chiller or evaporator
cho	=	water outlet from chiller
ch	=	evaporator
cond	=	condenser
geni	=	hot water (or steam) inlet to generator of an absorption machine

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APPENDIX A
ROOT MEAN SQUARE ERROR

How well a regression model fits the observations is quantified statistically by the well-known coefficient of determination (R^2) (see any statistical textbook, for example, Chatterjee and Price [1981]) and by the coefficient of variation (CV). While the former needs no explanation, the latter index needs a little discussion. The root mean square error (RMSE) of a model identified from data is defined as follows:

$$\text{RMSE} = \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-p}\right]^{1/2} \tag{A1}$$

where y is the response variable of the model, n is the number of observations, and p is the number of model parameters. The RMSE is an absolute measure and its range is $0 \le RMSE \le \infty$. A normalized measure is often more appropriate, the coefficient of variation of the RMSE (CVRMSE) or simply CV, defined as

$$\text{CV} = \text{RMSE}/\bar{y} = \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n-p}\right]^{1/2} / \bar{y}\,, \tag{A2}$$

where $\bar{y}$ is the mean value of the measured observations. Hence, a CVRMSE value of say 2% implies that the root mean value of the unexplained variation (i.e., the square errors about the model line) is 2% of the mean value of the dependent variable.

Reddy and Claridge (2000) point out that for determining energy savings from energy retrofits involving a baseline regression model, the CV is the better measure to consider since it has a direct bearing on the uncertainty of the energy savings determined. A brief look at Equation A2 reveals that the CV defined thus tends to place less emphasis on model-observation deviations, which occur at lower numerical values than at the high end. Consequently, the measure may inadequately represent the goodness of fit under such cases. An alternative definition of CV (which is much less used in the HVAC&R industry but has been used by Hydeman et al. 1999) is

$$CV^* = \left[\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)/y_i]^2}{n-p} \right]^{1/2} . \tag{A3}$$

It will be noted that CV* is analogous to the *chi-square test* widely used in statistics (see any basic textbook) that allows one to compare observed with expected frequencies and thereby test whether these are similar to within a stipulated significance level. If CV and CV* indices differ appreciably for a particular model, this would reveal that the model may be inadequate at the extremities of the range of variation of the response variable. Specifically, if CV*> CV, this would indicate that the model deviates at the lower range, and vice-versa.

APPENDIX B
DESCRIPTION OF CHILLERS AND CORRESPONDING RANGE OF DATA

Chiller Type	Chiller ID	Rated Capacity (ton)	Minimum/ Rated Cap (%)	T_{cdi} (°F)	T_{cho} (°F)	Refrigerant	Number of Data Points
Centrifugal chiller with inlet guide vane control	400	118	16.9	80	45	–	23
	397	120	10.8	80	45	–	29
	380	209	19.1	75	44	R-22	34
	354	219	23.3	75	44	R-134a	34
	370	246	9.3	75	44	R-134a	35
	395	257	8.6	70	45	–	28
	372	318	18.9	74.5	44	R-123	29
	369	320	9.4	76.8	44	R-134a	34
	375	326	9.2	77	44	R-123	35
	394	334	19.5	80	45	R-134a	29
	391	434	19.8	80	45	R-134a	29
	402	483	20.7	80	45	–	20
	363	521	19.2	75	44	R-123	33
	384	523	9.6	75	44	R-123	25
	362	545	18.3	75	44	R-123	35
	386	601	9.1	75	44	R-123	25
Centrifugal chiller with variable-speed drive control	371	154	39.0	76.8	44	R-123	29
	346	200	12.5	75	44	R-123	36
	378	203	19.7	75	44	R-134a	33
	392	229	19.2	80	45	R-134a	28
	350	257	19.8	75	44	R-134a	35
	357	275	23.6	80	45	R-134a	29
	377	324	19.4	75	44	R-134a	32
	376	326	9.2	77	44	R-123	35
	393	329	19.8	80	45	R-134a	28
	390	431	19.7	80	45	R-134a	27
	379	436	19.5	75	44	R-134a	33
	360	523	19.1	75	44	R-134a	35
	364	534	9.4	75	44	R-123	37
	361	537	18.6	75	44	R-123	33
Centrifugal chiller with variable condenser flow rate	358	375	28.8	85	44	R-123	52

APPENDIX B (Continued)
DESCRIPTION OF CHILLERS AND CORRESPONDING RANGE OF DATA

Chiller Type	Chiller ID	Rated Capacity (ton)	Minimum/ Rated Cap (%)	T_{cdi} (°F)	T_{cho} (°F)	Refrigerant	Number of Data Points
Screw chiller	381	152	29.6	75	44	R-22	28
	387	157	29.2	75	44	R-22	28
	382	158	29.1	75	44	R-22	28
	349	194	29.3	75	44	R-134a	27
	352	203	19.2	75	44	R-22	35
	344	210	11.4	75	44	R-123	28
	368	240	19.6	75	44	R-134a	34
	355	245	20	75	44	R-22	34
	373	297	28.6	76.8	44	R-134a	24
	353	307	20.5	75	44	R-22	35
	374	314	28.7	77.5	44	R-134a	25
	348	322	24.1	75	44	R-134a	27
Reciprocating chiller	290	48	41.7	85	44	R-22	27
	315	98	22.9	85	44	R-22	20
Scroll chiller	316	59	25.1	85	44	R-22	19
Absorption chillers (two-stage)	1	1000	34.3	-	-	LiBr-Water	20
	2	800	60.0	-	-	LiBr-Water	20
	Y1*	120	63.0	-	-	LiBr-Water	183
	Y2*	363	63.0	-	-	LiBr-Water	183
	Y3*	908	61.3	-	-	LiBr-Water	183

Note: T_{cho} and T_{cdi} in the table are the temperatures corresponding to rated cooling capacity
* From manufacturer catalogs