Characteristic Physical Parameter Approach to Modeling Chillers Suitable for Fault Detection, Diagnosis, and Evaluation

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Model-based fault detection and diagnosis approaches based on statistical models for fault-free performance concurrently require a fault classifier database for diagnosis. On the other hand, a model with physical parameters would directly provide such diagnostic ability. In this paper, we propose a generic model development approach, called the characteristic parameter approach, which is suitable for large engineering systems that usually come equipped with numerous sensors. Such an approach is applied to large centrifugal chillers, which are generally the single most expensive piece of equipment in heating, ventilating, air-conditioning, and refrigeration systems. The basis of the characteristic parameter approach is to quantify the performance of each and every primary component of the chiller (the electrical motor, the compressor, the condenser heat exchanger, the evaporator heat exchanger, and the expansion device) by one or two performance parameters, the variation in magnitude of which is indicative of the health of that component. A hybrid inverse model is set up based on the theoretical standard refrigeration cycle in conjunction with statistically identified component models that correct for non-standard behavior of the characteristic parameters of the particular chiller. Such an approach has the advantage of using few physically meaningful parameters (as against using the numerous sensor data directly), which simplifies the detection phase while directly providing the needed diagnostic ability. Another advantage to this generic approach is that the identification of the correction models is simple and robust, since it requires regression rather than calibration. The entire methodology has been illustrated with actual monitored data from two centrifugal chillers (one a laboratory chiller and the other a field operated chiller). The sensitivity of this approach to sensor noise has also been investigated. [DOI: 10.1115/1.1567317]

Background

With many engineering systems growing larger and more complex, the need to operate and control them safely and reliably has extended beyond the normally accepted safety-critical systems to being able to continuously operate them in an optimum manner [1]. As early as the 1960s, it was realized that faults in critical systems, such as nuclear power plants, space exploration, and weapon systems, could have grave consequences. Even a minor malfunction may cause the failure of the whole system resulting in loss of time, money, and even life. Such consideration led to research into Fault Detection, Diagnosis, and Evaluation (FDDE) supervisory systems in order to identify even relatively minor malfunctions as early as possible while emphasizing detection speed, sensitivity, and false alarm rate. Several textbooks have been written on this topic (e.g., [2–5]). This optimum performance of the system would involve reducing the occurrence of sudden, disruptive, or dangerous faults, i.e., minimizing system performance degradation, product deterioration, and equipment damage while improving human comfort and safety. FDD systems have also been studied under the rubric *condition monitoring*, whose purpose is to assist in the implementation of predictive maintenance as against the more common strategies of breakdown and planned maintenance [6].

However, the application of FDDE to HVAC&R equipment and systems is a relatively new field that has yet to acquire the maturity and sophistication gained in other engineering fields. This is borne out by fact that there are approximately two dozens papers on HVAC&R equipment and only about a dozen on chillers and unitary cooling equipment that pertain to FDDE. A source book by the International Energy Association [7], a review chapter by Katipamula et al. [8], and literature reviews by Comstock et al. [9], and by Reddy et al. [10] are the only review publications in the HVAC area.

Faults result in excessive energy consumption and increased environmental pollution. For example, it is common to find condenser fouling in a chiller penalizing the COP by 20–30%. Kao and Pierce [11] found that annual energy consumption in the air-handler of an HVAC system increased 50% as a result of an improper control sensor. Faulty operation also leads to equipment wear and/or noncompliance of the design conditions of the process or space to be conditioned, which could result in litigation. Existing Building Automation Systems are primarily meant to control or manage various building mechanical and electrical equipment so as to achieve optimal energy use or minimum operating costs. Such systems to-date lack sophisticated detection and sequence control capability of equipment such as chillers. On the other hand, the control and fault detection systems specific to the chillers are primarily meant to prevent mechanical failures. Other benefits of FDDE are reduction in unnecessary peak power demand and reduction of energy use.

A search for FDDE studies pertinent to chillers and unitary cooling equipment revealed that there are essentially only 12 studies on chillers and heat pumps, and three on unitary equipment [9]. None of these studies has dealt with field-operated equipment, being limited to laboratory equipment. Wagner and Soureshi [12]

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and Rossi and Braun [13] have used a forward model to train the baseline model, while the others have resorted to intentional introduction of known faults in the laboratory equipment in order to create the faulty-operation database necessary for fault diagnosis. There is a wide range in the number of variables that have been measured (from 76 to 3), while the sampling interval ranged from 6 sec to 1 min. The largest chiller was rated at 270 kW cooling capacity. The fault detection was mostly innovation based, while the fault isolation used either pattern recognition or a heuristic database. Three of the studies used model free pre-processors. Two of the studies were based on the use of Artificial Neural Networks (ANN). The FDD is performed by mapping direct measurement with a comparison database. Four of the studies evaluated two different types of fault detection pre-processors. Only Grimmelius et al. [14] have reported the implementation of a prototype condition-monitoring scheme for chiller FDD.

Traditional FDD methods adopted in the HVAC&R area generally involve measuring numerous performance variables, statistically detecting if one or more sensor data show a statistically significant deviation (this is the fault detection process), and then comparing the relative direction of change against pre-defined patterns embedded in a diagnostic classifier database (which is the fault diagnosis phase). Such an approach requires that fault detection be performed on numerous measured data channels (which is a statistically challenging step), but more importantly, that a diagnostic classifier database be generated and available for fault diagnosis. The latter is usually done by a series of intrusive tests during which known faults are intentionally introduced—an approach, which is totally unsuitable for large equipment operating in the field. Hence, a more scientific and practical FDD methodology is warranted for large engineering systems.

Objective and Scope

Large centrifugal single-stage chillers are typically the single most expensive piece of equipment in HVAC&R systems. They are well suited for FDD where the economic benefits of proper operation and control justify the added cost of the FDD system. A primary capability of having a FDD system in place is the ability to develop a model of the chiller and its sub-components that can be used to represent its fault-free behavior. Gordon and Ng [15] have proposed and validated a physical chiller model which can be applied to external fluid measurements and whose parameters directly relate to aggregate chiller characteristics (such as internal and external irreversibilities and heat leaks). Since most large chillers come equipped with an array of existing sensors installed by the chiller manufacturer, one could extend this approach. The objective of this paper is to propose and validate a new inverse modeling approach, called the *characteristic parameter approach*, which allows a baseline or fault-free model of the chiller to be identified from performance data. The basis of the characteristic parameter approach is to characterize each and every primary component of the chiller (the electrical motor, compressor, condenser heat exchanger, evaporator heat exchanger, and expansion device) by one or, at most, two performance parameters, the variation in magnitude of which is indicative of the health of that component. A hybrid inverse model is set up based on the theoretical standard refrigeration cycle in conjunction with statistically identified component models that correct for non-standard behavior of the characteristic parameters of the particular chiller. Such an approach has the advantage of using few physically meaningful parameters (as against using the numerous sensor data directly) that simplifies the detection phase while directly providing the needed diagnostic ability. Another advantage to this generic approach is that the identification of the correction models is simple and robust, since they require regression rather than calibration.

The scope of this paper is limited to steady-state modeling of the chiller. Under actual operation, driving conditions change continuously, and the chiller's operation can be broken up into either transient (start-up and shut-down) or steady state. Unlike small air-conditioners, large centrifugal chillers have much more stable driving conditions. The bigger the building being served by the chiller, the more likely are the driving conditions to be stable and slow in their diurnal changes. Because the time scale for temperature, pressure, and flow of the chiller to reach equilibrium is much smaller than the time scale of the driving conditions, it is reasonable to assume chiller operation to be quasi-steady-state, or stepwise steady-state. This is another way of saying that the time constants of a chiller are much smaller than that of a large building. According to Stylianou and Nikanpour [16], operation times under transient state are normally less than ten minutes for a small chiller of 25 kW. Discussions with experienced researchers in this area lead us to believe that large chillers will have time constants around 5–10 min. Thus, the chiller system can be assumed to be under steady state during the time step of simulation (assumed to be 15–30 min), and changes instantaneously to a new set of operating conditions when the driving conditions of the next time step are imposed. Although a quasi-steady state is an idealized process and is not an exact representation of an actual process, the operation process of large centrifugal chillers can be so modeled for the purposes of FDD because of the slow change in the driving conditions as compared to the time step of simulation.

Standard Refrigeration Cycle

The standard refrigeration cycle is well known, as described in several textbooks, for example, Stoecker and Jones [17] and Gordon and Ng [15]. Figure 1 shows a schematic of the single-stage vapor compression chiller. The theoretical standard refrigeration cycle presumes the refrigerant entering the compressor at state 1 to be saturated vapor. Both the enthalpy and pressure rise as the refrigerant passes through the compressor to a superheated state 2. The ideal process from 1 to 2 is assumed to be an isentropic compression process. In the condenser, the refrigerant is cooled and condensed at a constant pressure and exits at state 3 as saturated liquid. It is then expanded at constant enthalpy to the evaporator pressure (state 4). The refrigerant removes heat from the chilled water in the evaporator at constant pressure. The whole cycle consists of four processes described below.

a. 1-2. Isentropic compression in the compressor. The compression is assumed to be isentropic. The expression for the power input:

$$W_{in}=m_r(h_2-h_1) \tag{1}$$

b. 2-3. Heat rejection in the condenser under constant pressure. Heat transfer in the condenser is modeled using an overall conductance (UA) and the log-mean temperature difference $(LMTD)$. The pertinent heat balance equations are

$$Q_{cd}=m_{cd}c_p(T_{cdo}-T_{cdi})=(UA)_{cd}(LMTD)_{cd}=m_r(h_2-h_3) \tag{2}$$

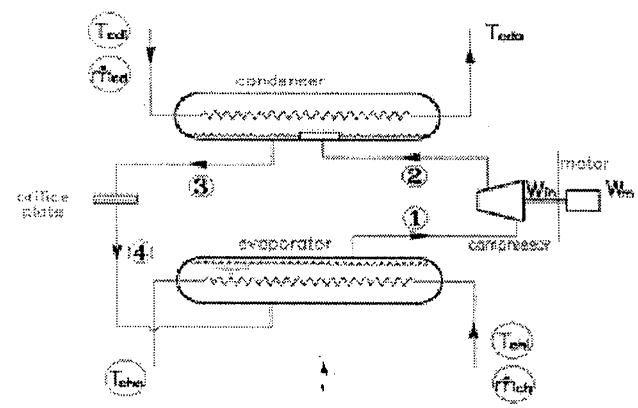

Fig. 1 Schematic Diagram for a Single-Stage Chiller

where

$$LMTD_{cd}=\frac{T_{cdo}-T_{cdi}}{\ln\left[\frac{T_c-T_{cdo}}{T_c-T_{cdi}}\right]} \tag{3}$$

In the expression for $LMTD$, it is not strictly correct to use T_c because of the superheat horn [15]. Refrigerant entering the condenser is superheated and is cooled sensibly to the saturation temperature at a relatively constant pressure prior to condensation. During this process, the heat transfer coefficient is lower and the temperature difference higher than during condensation. The conventional wisdom (recently questioned by [15]) is that these tradeoffs justify the use of a single condenser temperature and single condensing heat transfer coefficient in the model.

c. 3-4. Throttling in the expansion device under constant enthalpy. The thermal expansion device is meant to regulate the refrigerant flow, such that a saturated vapor state is maintained at the compressor inlet. The entering and exiting enthalpies of the expansion device are assumed to be equal.

$$h_4=h_3 \tag{4}$$

d. 4-1. Heat absorption in the evaporator under constant pressure. Heat transfer in the evaporator is modeled using an overall conductance and log-mean temperature difference. The heat balance equations are

$$Q_{ch}=m_{ch}c_p(T_{chi}-T_{cho})=(UA)_{ch}(LMTD)_{ch}=m_r(h_1-h_4) \tag{5}$$

where

$$LMTD_{ch}=\frac{T_{chi}-T_{cho}}{\ln\left[\frac{T_{chi}-T_e}{T_{cho}-T_e}\right]} \tag{6}$$

Modeling Actual Chiller Performance

There are a number of differences between standard and actual refrigeration cycles. Actual large chillers are usually designed with flooded evaporators and condensers. Further, depending on the actual cooling load, the refrigerant level in the shell-side of the evaporator varies in height such that the heat exchanger tubes may either be fully or partially submerged in the refrigerant liquid. The refrigerant entering the compressor at state 1 could be either superheated vapor or saturated vapor, depending on the refrigerant level in the evaporator. Assuming it to be saturated vapor may result in some error, especially when the refrigerant does not cover all the tubes inside the evaporator.

Both the enthalpy and pressure increase as the refrigerant passes through the compressor to a superheated state 2. The actual process from 1 to 2 is neither strictly an isentropic compression process nor a polytropical process. It is a process that may require more work than the polytropic process in order to achieve the same pressure increase. In the condenser, the refrigerant is cooled and condensed at a constant pressure. When there is no subcooling, the refrigerant at state 3 is close to saturated liquid. Since most large chillers have flooded condensers, process from 2 to 3 is very close to a constant pressure process. Refrigerant is expanded at constant enthalpy to the evaporated pressure (state 4) through the expansion device. Modulation to keep refrigerant saturated at the compressor inlet can be achieved by two methods: by adjusting the expansion device, or by adjusting the compressor inlet vanes. Centrifugal chillers under 3500 kW normally modulate the inlet vanes to control the capacity and use a fixed orifice plate for the thermal expansion device.

The modeling approach adopted should be tailored to suit the specific research objectives. There are three general methods to develop performance models of chillers:

a. the *empirical black-box* approach [17,18], where one fits empirical relationships to either performance or manufacturers' data. This is a very practical approach and is easy to implement. The limitation of this method is that the model can only be trusted within the range of conditions for which it was fitted, 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, [19]) can also be considered to fall in this category.

b. the *detailed mechanistic* approach [20–22], where one starts with a detailed knowledge of the physical geometry and construction of each of the sub-components 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 evaluate design alternatives in the physical manner in which sub-components are built, and in the way the whole chiller is operated. However, such an approach is not easily adapted to FD, since

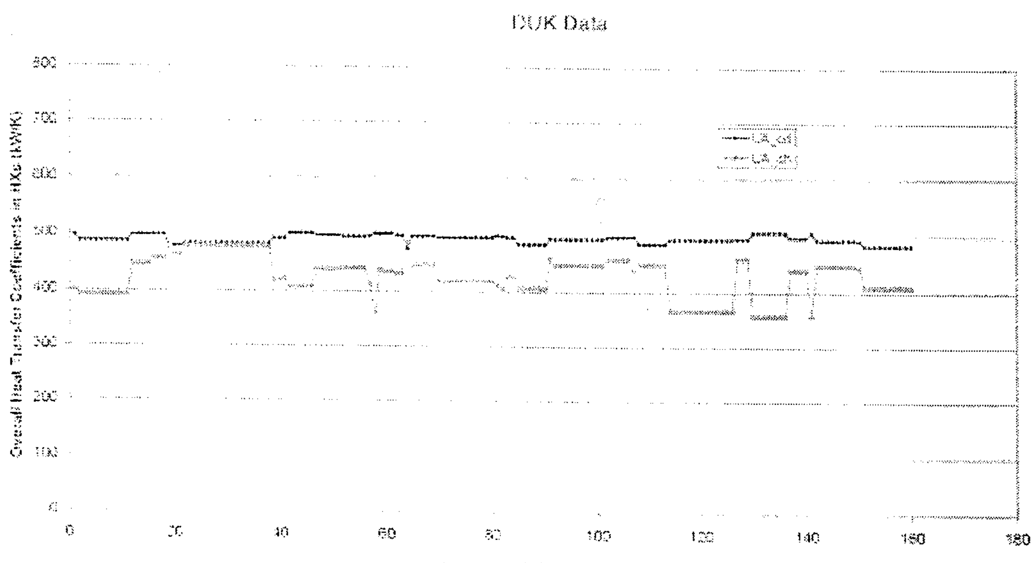

Fig. 2 Time series plots of the condenser and evaporator (*UA*) values determined from DUK chiller data (160 steady-state data points)

setting up the model is demanding, and calibration of this model with actual performance data is very complicated and tedious. Moreover, it is very likely that different analysts using the same basic modeling set of equations will calibrate it differently.

c. the *lumped physical model* approach, which relies on a simplified but scientific approximation of the performance of the system (for example, [23,15]). A variant is the *characteristic model* approach where models of the various components of the chiller are expressed in such a way that performance characteristic parameters of each component can be related to a particular type of fault, with the performance characteristic gleaned from monitored data. This type of "deconstruction" of the chiller has the potential to allow robust fault detection models to be developed during normal chiller operation. For example, to define the thermal performance of the condenser, the UA relationship with driving conditions is directly specified, and the modeling equations are formulated accordingly. Thus, our objective would be to use the simple model based on the theoretical standard refrigeration cycle complemented with characteristic component models, which can account for non-standard behavior of the components. Further, this approach would have the ability to calibrate the simulation model with performance data very easily, involving regression rather than calibration.

One of the requirements in using this model approach is that a relatively large set of variables be measured. Unlike small air-conditioners and rooftop units, large chillers come equipped with numerous manufacturer-mounted temperature sensors and pressure transducers. For example, large chillers have built-in chilled water supply and return temperature sensors, condenser water supply and return temperature sensors, refrigerant condensing and evaporating temperature sensors, and compressor discharge refrigerant temperature sensors. They also have built-in refrigerant condensing and evaporating pressure transducers. Connected properly to some interfacing equipment, they may automatically provide a complete set of chiller state and performance data. The instrumentation available should provide the necessary inputs to the physical component modeling approach and so the latter has to be structured accordingly.

Characteristic Parameter Modeling

Coefficient of Performance. Chiller manufacturers usually provide information about a chiller's design conditions in the form of tables of COP or power with cooling load Q_{ch} and chiller and condenser water inlet temperatures. The easiest way to detect a fault in the chiller's operation is to compare its performance with such tables. COP can be easily deduced from:

$$COP \equiv Q_{ch}/E \tag{7}$$

where, heat transfer rate in the evaporator can be determined from Eq. (5). The COP is not a constant but varies with the driving conditions, and so an appropriate model needs to be identified.

Compressor. The impeller of large centrifugal compressors is driven by an externally coupled electrical motor. There are two causes of inefficiencies external to the compressor: motor degradation (resulting in a lower power factor) and friction losses in the transmission (bearing friction of the shaft, etc.). Thus, not all electricity drawn by the motor is transferred to the chiller impeller. The ratio of power that is transferred into the chiller (W_{in}) to the electricity consumed by the motor is called *motor side efficiency*,

$$\eta_m \equiv W_{in}/E \tag{8}$$

Again η_m is not a constant, but depends on the driving parameters. It can be computed at each time step from the measured variables (assuming negligible heat losses):

$$\eta_m = (Q_{cd} - Q_{ch})/E \tag{9}$$

where the heat transfer rate in the condenser is given by Eq. (2).

One approach to modeling irreversibilities in the compressor is to use the adiabatic efficiency defined as the ratio of isentropic

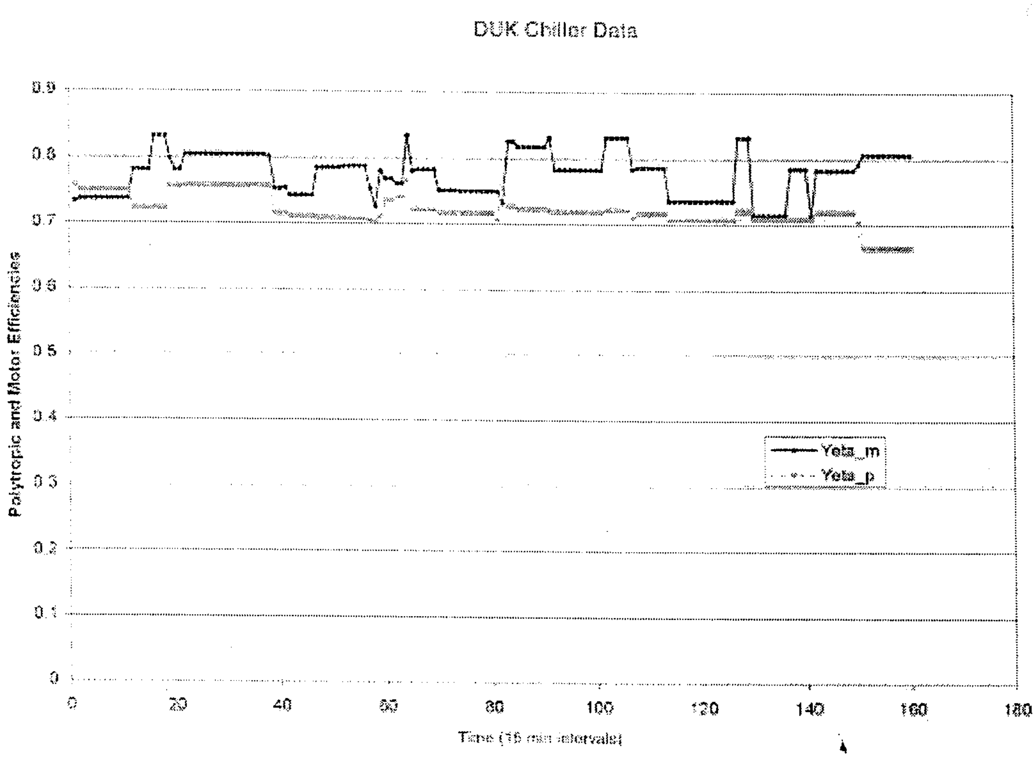

Fig. 3 Time series plots of the motor efficiency and the compressor polytropic efficiency values determined from DUK chiller data (160 steady-state data points)

Table 1 Results of step-wise regression (99% confidence level) of the characteristic component models using lab chiller data

Characteristic Parameter	Statistically Insignificant Model Parameters		Model R-square		Model Coefficient of Variation	
	Lab chiller	DUK Field chiller	Lab chiller (%)	DUK Field chiller (%)	Lab chiller (%)	DUK Field chiller (%)
UA (condenser)	a3	-	92	45	2.6	1.7
UA (evaporator)	a1, a2, a9	-	98	91	3.9	2.7
Polytropic efficiency	a6	a2	98	94	4.1	0.8
Motor efficiency	a4, a5	-	92	77	4.6	2.3
Friction coefficient	***	-	***	99.8	***	0.3

***Could not be identified due to incomplete data

Model used: $Y = a_0 + a_1 . T_{cdi} + a_2 . T_{cdi}\char`^2 + a_3 . T_{chi} + a_4 . T_{chi}\char`^2 + a_5 . T_{cho} + a_6 . T_{cho}\char`^2 + a_7 . T_{cdi} * T_{chi} + a_8 . T_{cdi} * T_{cho} + a_9 . T_{chi} * T_{cho}$

work to actual work. Though this is a useful first measure and is convenient for quick calculations, the drawback is that the same compressor produces different adiabatic results with different refrigerants, and also with the same refrigerant at different suction conditions. The preferred approach to compressor modeling is to use the concept of polytropic efficiency [24].

For a refrigerant vapor (which deviates from being an ideal gas), the polytropic compression process consumes the least amount of energy to attain a specified pressure difference. The ratio of power consumed by the polytropic process (W_p) to that consumed by the actual compression process (W_{in}) is called *polytropic efficiency*

$$\eta_p = W_p / W_{in} \tag{10}$$

This measure is an indicator of the health of the compressor. Distortions to the shape of the impeller's blade and base, the shape of the vane's blade and base and any change in surface smoothness during operation may affect η_p. When appropriate performance data are gathered, the values of the polytropic efficiency can be calculated at each time step as:

$$\eta_p = \frac{(p_2 v_2 - p_1 v_1)\ln(p_2 / p_1)}{(h_2 - h_1)\ln[(p_2 v_2)/(p_1 v_1)]} \tag{11}$$

Condenser and Evaporator. Though the condenser and evaporator are two different components, they are basically heat exchangers. The characteristic parameter selected to represent performance of the heat exchanger is the UA value. Experiments show that the UA values of condenser and evaporator are normally dependent on refrigerant level only if condenser water flow rate and chilled water flow rate are constant (which is usually the case). Refrigerant levels in the components change during operation.

The UA values are determined at each time step from the following equations:

$$(UA)_{cd} = c_p \dot{m}_{cd} \ln\left[\frac{T_c(p_2) - T_{cdi}}{T_c(p_2) - T_{cdo}}\right] \tag{12}$$

$$(UA)_{ch} = c_p \dot{m}_{ch} \ln\left[\frac{T_{chi} - T_e(p_1)}{T_{cho} - T_e(p_1)}\right] \tag{13}$$

where p_2 is the condenser pressure.

UA reflects the heat transfer efficiency of the heat exchanger. An abnormal UA value may indicate faults, such as excess fouling, tube leakage or excessively low water flow rate. Similarly, curves or a model of UA values with driving conditions can be generated for future use in fault diagnosis.

Expansion Valve. Many large centrifugal chillers do not have complicated expansion devices; often a fixed orifice plate is used as the throttle device with no moving part. The usual fault of the fixed orifice plate is partial blockage, which constricts refrigerant flow and degrades chiller performance. The characteristic parameter of this orifice plate is taken to be $C_d A_0$. The parameter C_d is the fluid friction coefficient and is a function of refrigerant velocity, i.e., of the refrigerant flow rate. When higher values of C_d are detected under the same driving conditions, this may suggest blockage of the orifice plate. A_0 is the total cross-sectional area of the orifice. Since these two quantities cannot be determined uniquely, our inverse model will take the product as a characteristic parameter. The characteristic parameter is calculated as:

$$C_d A_0 = \frac{\dot{m}_r v_3}{2\sqrt{p_3 - p_4}} \tag{14}$$

or, more completely as:

$$C_d A_0 = \frac{c_p \dot{m}_{cd}(T_{cdo} - T_{cdi}) - c_p \dot{m}_{ch}(T_{chi} - T_{cho})}{2[h_2(T_2, p_2) - h_1(T_1, p_1)]\rho_l(p_3)\sqrt{p_3 - p_4}} \tag{15}$$

where $\rho_l(p_3)$ is the density of the saturated liquid refrigerant at pressure p_3.

Empirical Correlations. As discussed earlier, these characteristic parameters are not constants but vary with operating conditions of the chiller. The final process in the development of the fault-free baseline model of the chiller is to identify corrective correlations to be applied to the standard refrigeration cycle for each of these characteristic parameters from the monitored data. Previous studies based on fundamental heat transfer and thermodynamic considerations (for example, Braun [20], Gordon and Ng [15]) suggest that the three following variables [Q_{ch}, T_{cdi}, and T_{chi}] are most pertinent for modeling part-load chiller performance. We thus propose that the following empirical correlations be determined from available experimental data when coolant flow rates are constant:

$$Y = f(Q_{ch}, T_{cdi}, T_{cho}) \text{ or } f(T_{cdi}, T_{chi}, T_{cho}) \tag{16}$$

where $Y = [COP, (UA)_{ch}, (UA)_{cd}, \eta_p, \eta_m, C_d A_0]$

Validation

Data from two centrifugal chillers are used in this study. The first is a set of 27 steady-state measured chiller performance data from a 90-ton (316-kW) laboratory chiller located at Purdue University [25]. The set of 27 steady-state measurements were taken under laboratory conditions under specified operating conditions. The second data set is from a 450-ton (1582-kW) chiller located at Drexel University (called DUK chiller). Data from this field operated chiller was collected at 1-min time intervals over 14 days in summer of 2000, to which a 15-min steady-state filtering scheme was applied in order to extract data representative of steady-state performance. A data set of 160 points is used in this study. Details of both chiller plants can be found in Reddy et al. [10]. Both chiller systems consist of a shell-tube evaporator, a shell-tube condenser, a centrifugal compressor, and pilot-driven expansion valve for the lab chiller and a fixed orifice for the DUK chiller. Capacity control for both chillers is achieved by varying the compressor's inlet-guide-vane angles.

The five characteristic parameters for both chiller data sets are first calculated for each set of operating conditions. Note that the friction coefficient term for the lab chiller could not be identified due to lack of corresponding monitored variables. The variation of the two UA values and the two efficiency parameters for the DUK chiller, shown in Figs. 2 and 3, seem to be about 15–20%. Multivariate polynomial regression models given by Eq. (16) were fitted to the data sets using stepwise regression with 99% confidence level in parameter retention. The regression fits are generally very good (model $R^2>90\%$, and CV values about 2%) as can be noted from Table 1. A notable exception is the motor efficiency, which is poor. This is not unexpected because heat losses from the chiller have been neglected in formulating Eq. (9). A visual representation of how well the model captured the variability in the lab chiller data is illustrated in Fig. 4. We can thus conclude that the choice of the model given by Eq. (16) is justified.

A further verification into how well the joint use of the standard cycle equations and the characteristic physical component approach is able to predict additional measured variables has also been done. The close agreement of all measured variables and the model predicted values is clearly illustrated in Fig. 5 for the lab chiller, thus providing another means of indirect justification of the entire modeling procedure advocated.

Sensitivity to Sensor Noise

Evaluation of model sensitivity to measurement noise has been done based on a *propagation of error analysis* [26]. This involves ascertaining whether the uncertainty in the chiller characteristic parameters arising from sensor noise is acceptable, and how it changes with operating conditions (e.g., with chiller loading).

A data logger usually samples data more frequently than the recording time scale. Though data loggers may scan once every few seconds, a time scale of 1 min represents the lower bound of the commonly adopted time scale for data recording. To a first approximation, let us assume that the sensor data, which is recorded every 1 min, has the same uncertainty as that reported by the sensor manufacturer. However, from a practical point of view, a 15-min time scale is more appropriate for data storage and analysis. Since an average is involved, one would expect the measurement uncertainty of this 15-min value to be less than that of the 1-min value. How much less would depend on the serial correlation exhibited by the 15 observations in each block. The serial correlation must be determined from measured data, which can be used to compute the number of *independent* data points. One cannot arbitrarily assume a reduction equal to ($1/N^{1/2}$) where N is the number of independent observations, since this applies *only* when the data are random. Measurement errors tend to become correlated as a result of high sampling capability of automated digital data acquisition equipment. Rather than arbitrarily assuming one (or a few) correlation coefficients, we have chosen to present the results of the uncertainty analysis by calculating two bounds: *i.* due to individual measurements representative of the conservative (i.e., high) bounds, in which case $N=1$, and *ii.* due to multiple measurements representative of the optimistic (i.e. low) bounds, in which case $N=15$.

Four kinds of measurements are involved in this study: temperature measurement, pressure measurement, mass flow-rate measurement, and electrical power measurement. Two sets of sensors with different accuracy corresponding to commercial grade and industrial grade have been selected. Typical accuracy values of well-maintained instrumentation for a 1500-kW chiller (with COP around 4–5) are given in Table 2.

The 95% uncertainty bands for the five characteristic parameters, as well as those for the COP, have been computed for chiller loading of 0.3 and 0.6 using both industrial and commercial grade sensors and for both cases of individual or single measurements and when a 15-min average value is selected (see Figs. 6 and 7, respectively). If a fault detection scheme based on the characteristic parameter approach is to be sensitive, one would like the y-axis, denoting the relative uncertainty, to be low (say, less than 0.10–0.15). It is clear from Fig. 6 that uncertainty bands of all quantities (except perhaps the COP and the polytropic efficiency) based on single measurements are generally high, and would be unacceptable for FD purposes. Using industrial grade sensors alleviates this problem somewhat, but the relative uncertainties are still high (Fig. 6). A possible recourse under commercial grade instrumentation is to use 15-min averages in our FD process (see Fig. 7). Even then the relative uncertainties of certain characteristic parameters such as η_m and the friction coefficient are high at 60% load fraction. (Note that the former is consistent with the statistical analysis shown in Table 1). Only under industry grade multiple measurement scheme are the relative uncertainties low enough to be acceptable from a practical viewpoint for implementing the FDDE scheme. Another option to lower the relative uncertainty is to use averages of 30 points instead of 15 points.

The uncertainty analysis summarized by Figs. 6 and 7 also provides insight into another practical issue. To simplify the fault detection process, one approach is not to track all the characteristic parameters but to track only the one which is the most mean-

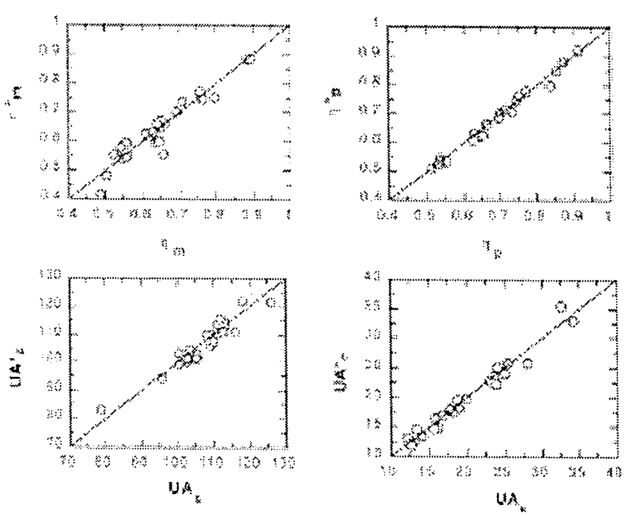

Fig. 4 Measured and regression model-predicted lab chiller characteristic parameters

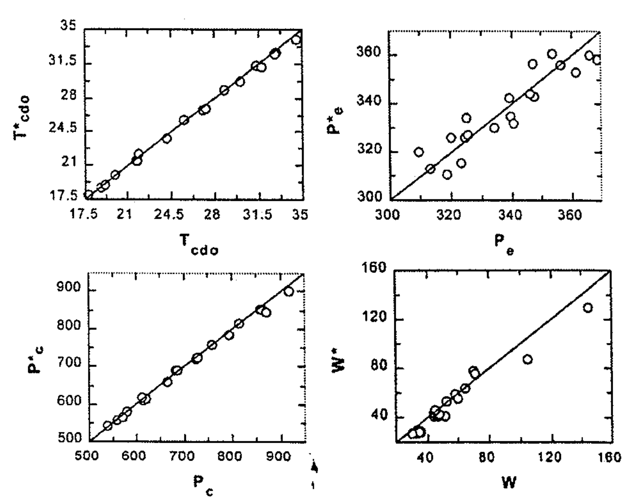

Fig. 5 Measured and predicted lab chiller performance data

Table 2 Assumed sensor accuracies for a typical 1500 kW chiller

Type	Industrial Grade	Commercial Grade
Temperature	0.05°C	0.1°C
Pressure	7 kPa	14 kPa
Flow	2% of Full Scale	4% of Full Scale
Power	3 kW (about 1% of full scale)	6 kW

ingful and has small uncertainty bands. Only when a potential faulty condition is flagged by tracking this parameters does one look at the remaining parameters in order to support (or disprove) the onset of a fault, and to diagnose the fault. This process is called a *two-stage FDD scheme*, which will be addressed in a future paper. It is clear that COP is the most sensitive and would be the logical choice as the primary parameter for a two-stage FDD process. (Note that though polytropic efficiency seems to have less relative uncertainty, COP is a better measure of the overall chiller condition).

Conclusions and Summary

Manufacturers of large chillers provide, at no extra expense, the capability of gathering performance data from numerous sensor points already installed on their equipment. Hence the characteristic parameter approach is particularly suited towards such equipment since no additional expense need be incurred. The modeling approach is an inverse hybrid model in the sense that it complements the well-known standard refrigeration cycle analysis models with a set of component correlations that are identified by regression from performance data which account for non-standard behavior of the chiller thermodynamic cycle. Both fault detection

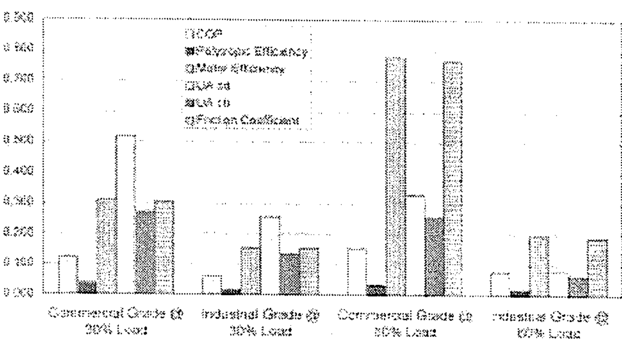

Fig. 6 Summary plot of the relative uncertainty at 95% CL defined as the ratio (standard error/estimate) of the various characteristic parameters under different sensor grade types (commercial or industrial) for load factor values of 0.3 and 0.6 using single measurement point

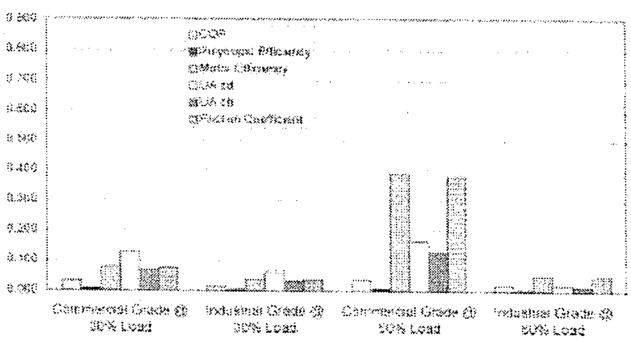

Fig. 7 Same as Fig. 6, but for multiple measurements of 15 points

and diagnosis phases are simplified, since there are few physical parameters to track, and any deviation from their fault-free condition directly provides the necessary diagnostic ability. Validation of this modeling approach is also presented using monitored data both from an actual laboratory chiller and a field operated chiller. Finally, the sensitivity of this approach to sensor noise has been discussed and illustrated with a typical case study.

Future work would involve studying the practical issues in implementing such a FDD scheme on a routine basis. More generally, the extent to which this generic approach can be applied to other engineering systems also needs to be investigated. The basic concept behind the characteristic physical parameter approach is to identify physically meaningful performance indices of the equipment, which can be directly determined or computed from the basic measurement set without having to use a model of any sort. Hence, though this approach can, in principle, be applied to other types of chillers (say, reciprocating, or even heat pumps and absorption chillers) as well as other thermal and mechanical equipment (I.C. engines, gas turbines, pumps, etc.), the selection of the appropriate physical parameters would depend on the specific type of basic measurement available. In that regard, the proposed modeling approach needs to be tailored to the specific circumstances.

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Nomenclature

A_0 = cross-sectional area of the orifice
COP = coefficient of performance
c_d = fluid friction coefficient
c_p = specific heat at constant pressure
E = electric power
h = enthalpy
$LMTD$ = log-mean temperature difference
m = mass flow-rate
p = pressure
Q = heat exchanged
T = temperature
UA = overall heat conductance
W = work
η = efficiency
ν = specific volume
ρ = density

Subscripts

c = condenser side refrigerant
cd = condenser water side
cdi = condenser water inlet
cdo = condenser water outlet
ch = chilled water side
chi = chilled water inlet
cho = chilled water outlet
e = evaporator side refrigerant
in = inside, transferred in
l = liquid
m = motor side
p = polytropic
r = refrigerant
1,2,3,4 = state points as defined in Fig. 1

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