2016

A Prediction Method for Overall Economic Value of Fault Detection and Diagnostic Tools for Rooftop and Split Systems

David Yuill
University of Nebraska - Lincoln, United States of America, dyuill@purdue.edu

James Braun
Purdue University, United States of America, jbraun@purdue.edu

A Prediction Method for Overall Economic Value of Fault Detection and Diagnostic Tools for Rooftop and Split Systems

David P. YUILL[1]* and James E. BRAUN[2]

[1]University of Nebraska – Lincoln, Architectural Engineering
Omaha, NE, USA
(402) 554-4176, dyuill@unl.edu

[2]Ray W. Herrick Laboratories, Purdue University, Mechanical Engineering
West Lafayette, IN, USA

* Corresponding Author

ABSTRACT

Fault detection and diagnostics (FDD) tools for air-conditioning application may perform well or poorly, but it is difficult to characterize this performance in a meaningful way. Some recently proposed evaluation techniques have provided various statistics to characterize FDD performance, but these results can be difficult for a potential adopter of FDD to understand. A new method of characterizing FDD performance by predicting the overall economic value of the FDD tool is proposed in this paper. It is applicable to FDD tools intended for air-cooled unitary air-conditioners, such as rooftop units (RTU) and split systems. The method gives an estimated dollar value, normalized per nominal ton of capacity, for a specific FDD tool when applied in a typical scenario. This is accomplished by considering a large set of variables that affect the tool's value: probabilities of fault occurrence (both type and intensity) and operating conditions during FDD deployment; energy impact of each fault scenario; fault-induced loss of equipment life, and costs associated with addressing faults. Some case studies of FDD tools currently in use are presented to demonstrate the method. These tools have a surprising range of value.

1. INTRODUCTION

Fault detection and diagnosis (FDD) tools have the potential to provide operators with early warning of degradation faults that can reduce capacity, efficiency and life expectancy of equipment. Many FDD methods for air-conditioning equipment have been proposed and adopted commercially (Bonvini et al. 2014, Cho et al., 2014, Du et al. 2016, Mulumba et al. 2015, Wiggins and Brodrick 2012, Xiao et al. 2014). Yuill and Braun (2012, 2013) argue that the performance of FDD tools should be quantified, and proposed a standardized method for evaluating the performance of one category of FDD tool: handheld tools applied to air-cooled unitary air-conditioning systems. These tools use measurements of system variables gathered during a technician visit (as opposed to onboard sensors gathering data over time). The method feeds laboratory measurement data from several split systems and rooftop units to the candidate FDD tool, and compares the tool's response to the known fault condition. To fully characterize the performance, the input data library contains a wide variety of expected fault types, fault intensities, and operating conditions. Yuill et al. (2014a) proposed using simulation data from fault-enabled gray-box models of unitary systems developed by Cheung and Braun (2013a, 2013b), and Yuill et al. (2014b) validated these models for use in FDD tool evaluation. Finally, Yuill and Braun (2016a) show that simulation-based evaluation of FDD tools is more effective than evaluations conducted using laboratory measurements.

One shortcoming of the evaluation methods described above is that the results can be difficult to interpret. The results are categorized according to a taxonomy of outcomes that include (a) No Response; (b) False Alarms; (c) Misdiagnoses; (d) Missed Detections; (e) No Diagnoses; and (f) Correct Diagnosis. Statistics for each of these outcomes are generated, based upon the fault's effect on system capacity and efficiency at each set of operating conditions. While these results give insight into an FDD tool's performance, they do not answer a key question for a potential adopter of the tools, which is: should I adopt this tool? Typically, the answer to this question depends primarily on the costs and benefits of adopting a tool, but these costs and benefits are difficult evaluate if based only upon metrics such as the percentage of False Alarms, for example. To address this shortcoming, the currently proposed methodology includes a holistic analysis of the costs and benefits of applying a candidate FDD tool, and gives a simplified result: an economic value of typical net benefit for a single application of the tool. This is accomplished using probability distributions, economic data, and results from a wide array of inputs fed to the FDD tool. A case study will be used to illustrate the method and draw general conlusions, with assumed values for the required inputs. Users of the method may substitute their own values if they're available. Additional details of this method are presented in Yuill and Braun (2016b).

2. METHODOLOGY

The overall economic value of a given FDD tool for an application is quantified using a hypothetical situation, in which a technician on a routine site visit will either use the FDD tool, and respond to its output (e.g. add refrigerant for a diagnosis of undercharge), or the technician will simply clean the condenser coil and replace the filter (or otherwise address evaporator airside fouling). A probability distribution to quantify the likelihood of a given fault type at a given fault intensity (or no fault) is applied, and combined with the probability of a given outdoor temperature (based on weather data for a given location). The indoor conditions could also be varied, but in the present analysis, they aren't, since they tend to not vary too significantly. The inputs include only scenarios in which a single fault (or no fault) is present, because there are currently no known data on the prevalence of multiple simultaneous faults in the field, and no reliable methods for modeling them.

To calculate the economic value of applying an FDD protocol, a large set of input conditions is fed to the protocol, and a cost and/or benefit is calculated for each one. For example, if the FDD diagnoses an undercharge of refrigerant, the cost is the cost of the technician adding refrigerant (labor and materials). If the diagnosis is correct, then the benefits include the reduction in energy usage over time and reduction in runtime (hence reduced equipment wear). One required component of this analysis is the fault impact ratio (FIR), which is defined for efficiency and capacity respectively as $FIR_{COP} = COP_{faulted}/COP_{unfaulted}$ and $FIR_Q = Q_{faulted}/Q_{unfaulted}$ in Yuill and Braun (2013). As noted above, the baseline case assumes that the technician cleans the coils and performs no further service. In this baseline case, there is a small cost associated with the service, and benefits accrue only for those cases with airside coil fouling. In each scenario the difference, β_θ, between the FDD's net costs and benefits, and the baseline's net costs and benefits, $\beta_{baseline}$, gives a net value of the FDD tool. This difference is weighted according to the probability of each scenario, and the differences are summed to give an overall value, V, for a given FDD tool, θ, as described in Eq. 1.

$$V(\theta) = \sum_i \sum_j \sum_k \sum_l P_{i,j,k,l} \cdot (\beta_\theta - \beta_{baseline})_{i,j,k,l} \tag{1}$$

The subscripts refer to the specific air-conditioner (i), the fault type (j), the fault intensity (k), and the ambient temperature (l). Yuill et al. (2014a) use a data library that includes 8 air-conditioners, 7 fault types, 3 to 7 fault intensities for each fault type, and 5 outdoor temperatures, ranging from 65°F to 115°F (18.3°C to 46.1°C). This same library is used in the case study presented below.

The value, V, is calculated using monetary units, such as dollars, and is normalized on the basis of equipment capacity. For example, in the U.S., V is expressed in \$/ton.

2.1 Calculation details

To contribute to the realism and universality of the method, there are many intricate details that must be addressed in the calculation. The first is how to deal with each outcome, such as False Alarms. In the case of a False Alarm – meaning that a fault is annunciated by the FDD when no significant fault is actually present – the technician is assumed to address the fault (adding service cost), but to not degrade the performance of the system. This could represent either an unnecessary adjustment, such as cleaning a clean coil, or a situation in which the technician realizes the diagnosis is incorrect after doing some work on the system, such as adjusting charge, and returns the system to its unfaulted state.

Some FDD tools will annunciate a fault detection, but may not diagnose the location or type of fault (classed as a "No Diagnosis"). In this case the technician is assumed to have some probability of correctly diagnosing and addressing the fault. Yuill and Braun (2016b) adopt a probability distribution as a function of fault intensity.

2.1.1 Benefits of addressing a fault: When a fault is correctly diagnosed, there can be a benefit to addressing it. In general, a fault, f, is assumed to reduce equipment life in comparison to the unfaulted case, u, by reducing capacity, Q, which increases runtime, RT, to meet a given building load, as shown in Eq. 2. An unfaulted air-conditioner is assumed to have a finite life expectancy, in runtime hours, and an associated replacement cost, $Cost_R$.

$$RT_f = \frac{RT_u}{FIR_Q} \tag{2}$$

Refrigerant overcharge must be given special treatment, because this fault can potentially increase capacity in some systems, but can have a detrimental effect on compressor life because it increases the potential for compressor slugging. A factor, α, is used to adjust expected equipment life, L, proportionally to the deviation in fault intensity, FI, for a given fault type, ϕ, for faulted cases, as shown in Eq. 3. This factor could be applied to other faults that are known to cause equipment degradation greater than adding runtime for decreased capacity.

$$L_f = L_u\left(1 - \alpha_\phi\left(FI_{\phi,f} - FI_{\phi,u}\right)\right) \tag{3}$$

Runtime could be calculated using a building energy simulation tool. However, simplified energy estimation methods, such as bin methods, are sufficient for most cases because (a) buildings served by unitary systems typically have cooling loads dominated by ventilation and envelope (hence the load is closely related to outdoor temperature), and (b) any additional uncertainty associated with simplified methods will not have a significant impact on the overall uncertainty of the FDD value, V. From runtime, the energy usage, E, can be calculated using efficiency (for both faulted and unfaulted cases), and multiplied by the local electricity rate, $Cost_E$, to get monetary cost of energy.

A key variable to be selected is τ, the time under consideration. τ represents the persistence of benefits. A longer time period will make FDD more valuable, since additional energy usage and equipment wear would accrue if a fault goes unnoticed for a longer period. τ could represent the time until service will next be applied (e.g. one year), or if the equipment will be run to failure, it could represent the total equipment life expectancy. However, τ is likely to also affect the probability of a fault being present (discussed below), so it should be chosen carefully.

With each of the costs imposed by a fault quantified, the benefit of addressing a fault can be calculated. Using a bin method for energy calculation, this benefit, B, is calculated for each considered temperature bin, b:

$$B_b = \left(\left(\frac{RT_f}{L_f} - \frac{RT_u}{L_u}\right) \cdot Cost_R + \left(E_f - E_u\right) \cdot Cost_E\right) \cdot \tau \tag{4}$$

2.1.2 Costs of service: There are one-time costs of providing service, C_S, for the baseline's routine coil cleaning and for any fault that is annunciated by the FDD. The cost includes service and materials, but for calculation simplicity the material costs are added as additional labor for each fault type. The labor hours associated with addressing each fault are taken from Li and Braun (2007), and are shown in Table 1.

Table 1: Fault types and labor hours to address them

Fault Type (ϕ)	Abbreviation (ϕ)	Labor Hours (h_s)	Fault Type (ϕ)	Abbreviation (ϕ)	Labor Hours (h_s)
No Fault	NoF	0	Liquid line restriction	LL	5
Undercharge	UC	3.5	Non-condensable gas	NC	3.5
Overcharge	OC	3.5	Comp. valve leakage	VL	9
Evaporator airflow	EA	0.5	TXV problem	TXV	5
Condenser airflow	CA	0.5			

As noted above, assumptions must be made about the probability of a service technician correctly diagnosing a fault if the FDD gives a No Diagnosis annunciation. This probability is used in the calculation of the net cost of a No Diagnosis, C_{ND}. There are also service labor cost ramifications for FDD tools that cannot be applied under certain conditions, or output “No Response”, C_{NR}. In the case study presented below, an additional half hour of labor is associated with No Response, to represent, for example, a technician returning later or hooking up gauges and sensors needlessly. These three costs are normalized by the capacity of the system, Q_{nom}, to give total cost, C:

$$C = \frac{(C_S + C_{NR} + C_{ND})}{Q_{nom}}. \tag{5}$$

2.2 Calculating overall value

The net benefit, β, can now be calculated as the difference between the benefits, B, and the costs, C.

$$\beta = B - C \tag{6}$$

In the baseline case – the technician addresses evaporator and condenser airside problems – an hour of labor is expended (see Table 1) and benefits accrue for all cases in which these fault types are present, calculated with Eq. 4.

The net benefits are calculated for each of the cases in the input data library for the FDD, β_θ, and for the baseline case, $\beta_{baseline}$, to use in Eq. 1. Each of the results is then weighted by its individual probability of occurrence, P.

2.2.1 Probability distributions: Four probabilities must be quantified to solve Eq. 1. The first, P_i, is the probability of a specific air conditioner in the data library reasonably representing an air-conditioner that the FDD will be deployed on. This could be used to evaluate performance of a subset of the units in the library, such as split systems only, units with TXVs only, etc. In the case study below, each of the eight air-conditioners is deemed equally representative, so P_i = 12.5% for i = 1:8.

The second and third probabilities, P_j and P_k, represent the probability of a given fault being present, and its intensity, respectively. Currently, there are no known reliable data for fault prevalence (i.e. occurrence of faults in the field, by type and by intensity). Therefore, assumed probability distributions were developed for the demonstration of the method. These distributions are shown in Table 2, using fault intensities (FI) as defined by Yuill et al. (2014a). P_j are shown on the left, and for each fault type, P_k are shown on the right. For example, it’s assumed that there’s a 7% chance of overcharge, and that 26% of overcharge cases will have a fault intensity of 120%.

Table 2: Probabilities of fault type, P_j, and fault intensity, P_k

Fault	P_j
NoF	39%
UC	10%
OC	7%
EA	13%
CA	16%
LL	5%
NC	5%
VL	4%

Fault	FI	P_k
UC	70%	16%
	80%	28%
	90%	56%
OC	110%	65%
	120%	26%
	130%	10%
EA	45%	8%
	60%	20%
	75%	31%
	90%	41%

Fault	FI	P_k
CA	40%	5%
	50%	11%
	63%	19%
	77%	27%
	90%	38%
LL	50%	31%
	100%	24%
	300%	16%
	600%	12%
	1200%	8%
	2000%	6%
	3500%	3%

Fault	FI	P_k
NC	10%	40%
	30%	28%
	55%	20%
	80%	10%
	100%	2%
VL	10%	45%
	20%	25%
	35%	18%
	50%	13%

The fourth probability, P_l, is the probability of a given temperature bin occurring. It's calculated by dividing the number of hours in a temperature bin (derived from typical meteorological data) by the number of hours when a technician might be on a service visit. For the case study below, this is the sum of all hours between 6 AM and 7 PM for which outdoor air temperature is above 15.6°C (60°F).

For each hour the net benefits ($\beta_\theta - \beta_{baseline}$) are multiplied by the probabilities, P, and the sum of these values constitutes the net total value per ton of nominal capacity, V_θ, of applying the FDD tool in this scenario as shown in Eq. 1.

3. CASE STUDY

A case study was carried out to assess the value, V, for eight FDD protocols. Six of these are existing protocols, labeled A1 to A6, that have seen widespread usage, and were either available publicly or were obtained from the developers on condition of anonymity. The remaining two are fictitious protocols that are intended to illustrate important facets about FDD evaluation. The first fictitious protocol is labeled "Correct"; it correctly detects and diagnoses every fault. The second is labeled "Ideal"; it annunciates only those faults that are cost-effective to address, given the assumptions and parameters of the given evaluation. In other words, minor faults, whose repair cost outweighs the net present value of the benefits that will accrue over time, are tolerated.

Some of the inputs for the value calculation are specific to the geographical location. In particular, weather data, which affect equipment runtime and the distribution of ambient temperatures, and local utility rates, will each affect the result. The evaluation of the eight FDD protocols has been repeated for four US cities with diverse weather and utility rates to illustrate this variation (Omaha, NE, Miami, FL, Minneapolis, MN and San Francisco, CA). Table 3 shows the input values that were used in the Omaha analysis for this case study. An inflation adjustment was applied to the data from Li and Braun (2007), which were gathered in 2004.

Table 3: Constants used in case study

Description	Source	Abbr.	Value	Units
Installed equipment cost	Li & Braun (2007)	$Cost_R$	$1109	$/ton
Equipment life (unfaulted)	Li & Braun (2007)	L_u	12000	hours
Service labor rate	Li & Braun (2007)	ρ_s	$82	hour^{-1}
Inflation since 2004	Bureau of Labor Statistics		26%	
Time under consideration	User-defined	τ	1	year
Electricity cost per kWh	Local utility	$Cost_E$	$0.10	kWh-1
Total hours in bins	TMY2	h_T	2,954	hours

For this analysis the evaporator entering air is assumed to be at 25°C (77°F) dry bulb, and 18.3°C (65°F) wet bulb temperature. This value is of importance for the FDD tool's performance, but typically FDD protocols work best within a reasonable range of evaporator inlet conditions, and suffer under more extreme conditions, such as dry coil operation (low dewpoint temperature). The runtime hours are not affected by the entering air temperature because the simplified calculation method is based on an assumed load profile, not specific indoor conditions. If different conditions were assumed, it is anticipated that the results would change very little unless they were extreme conditions, in which case FDD performance would degrade. The resulting economic values calculated for each of the eight FDD protocols applied in each of the four US cities are presented in Figure 1.

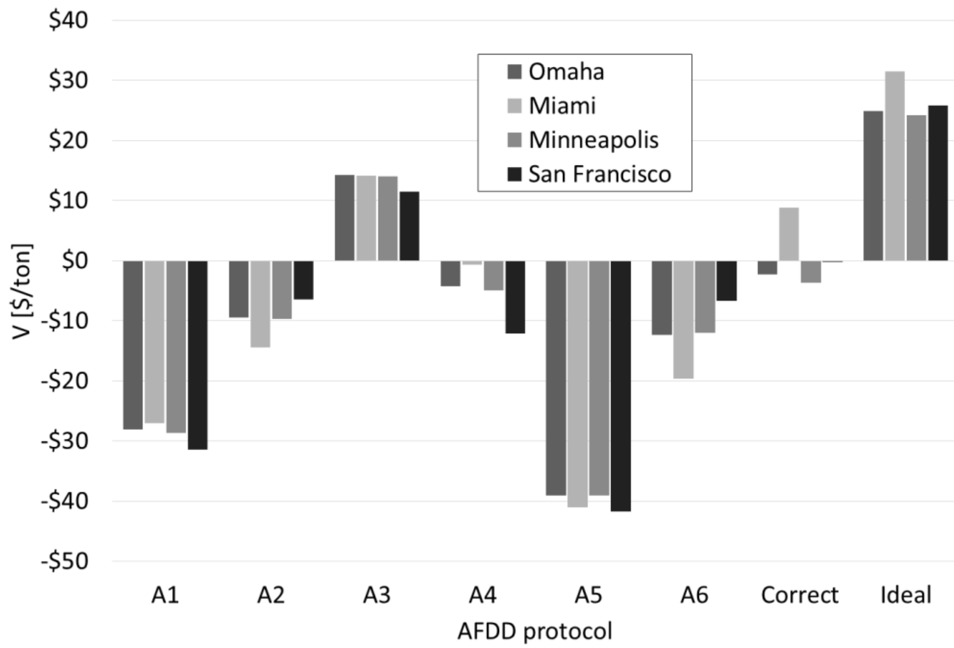

Figure 1: Overall economic value, *V*, for eight FDD protocols applied in four US cities

4. DISCUSSION OF RESULTS

Of the six actual protocols, A1 to A6, five of them give negative results. This is quite disappointing. It means that for these protocols, a service technician is better off using the baseline service (cleaning coils and making no measurements) than using the FDD tool. Furthermore, the magnitude of these results is quite large in some cases, meaning that there are very significant costs to deploying those protocols – up to $41/ton – and that even with minor uncertainties in the inputs, the true values can be assumed to be negative.

Some insight into the reason for these negative results can be seen in the Correct result. For this fictitious protocol, every fault is detected, diagnosed, and addressed. In only one of the cities, Miami, does this approach pay off. Miami is characterized by a large amount of annual runtime, so that performance improvements from addressing faults pay off more quickly. For Omaha and Minneapolis, the cost of addressing all faults doesn't pay off within the time period under consideration, $\tau = 1$ year. Although San Francisco has less run time (because of its mild climate) it has significantly higher electricity costs, so that for the Correct protocol, the value is approximately $0/ton.

How does protocol A3 manage to achieve results that are significant better than the Correct protocol? It does this by tolerating faults that are not cost effective to address. In Yuill et al. (2014a) this same protocol was evaluated using the method of Yuill and Braun (2013), and found to have a high rate of Missed Detections and a low rate of False Alarms. It uses a higher threshold of tolerance for faults. To be able to achieve these results, it's likely that A3 also considers the cost of addressing each fault type in its decision to annunciate faults.

The Ideal protocol represents the maximum economic value that could be achieved under the set of assumptions used in this evaluation. Protocol A3 typically achieves about $^2/_3$ of this maximum. Part of the value of the Ideal protocol is the avoidance of the baseline service – cleaning the coils – for those cases in which the coils don't require cleaning.

One mechanism for giving negative economic value is occurrence of misdiagnoses, because service is applied, but no benefits accrue. As noted above, it is assumed that system performance is not degraded by misdiagnoses.

One surprising result in Figure 1 is that V for most of the real protocols is not particularly sensitive to the city. Particularly for the best performing – A3 – and worst performing – A5 – the results are roughly identical for each city. This suggests that the results of the evaluation are not particularly sensitive to the equipment costs or energy costs, which vary significantly among the cities. Therefore we can conclude that the realism of the assumptions that contribute to the calculation of energy and equipment wear is not crucial.

One key value whose realism is crucial to meaningful evaluation is fault prevalence. The economic value, V, is strongly related to fault prevalence. For example, if there are no faults, the only value FDD can provide is avoidance of unnecessary service. This underscores the importance of gathering reliable fault prevalence data.

A second key value that should be considered carefully is the time under consideration, τ, which is proportional to the benefits in Eq. 4. This value should be considered independent of the analysis. For example, determination of an improved maintenance schedule based upon calculating V for varying values of τ wouldn't provide useful results, because increasing values of τ will always give increasing V. Instead, this should be interpreted as: if a long time between service visits is expected, then there will be more value in using an effective FDD tool.

5. CONCLUSIONS

A methodology for calculating the total economic value of applying a given FDD tool during a routine service call has been summarized in this paper, and demonstrated with a case study of several FDD tools. The following conclusions can be drawn from this discussion:

- Many of the currently existing FDD protocols don't perform as well as one would hope. Five of six protocols that are in current use were shown to add costs to a routine service visit that exceed the benefits that they bring. This result underscores the need to evaluate FDD protocols prior to adopting them.
- Some protocols are able to provide very strong positive value. FDD, therefore, should continue to be developed and should be adopted more widely.
- An important consideration in the development of FDD tools is fault tolerance
- The case study results are plausible, and are insensitive to some of the many assumptions that must be included in the calculation. However, one exception is the assumed fault prevalence distributions, to which the value, V, is quite sensitive. There is a need for reliable fault prevalence data.

NOMENCLATURE

A	Existing FDD protocol		FXO	Fixed orifice expansion device	
B	Benefit of service	($/year)	h	Hours	(hours)
C	Cost	($)	L	Equipment lifetime	(hours)
COP	coefficient of performance	(–)	LL	Liquid line restriction fault	
E	Energy consumption	(kWh/ton)	NC	Non-condensable gas fault	
EA	Evaporator airflow fault		OC	Overcharge fault	
FDD	Fault detection and diagnosis		P	Probability	(–)
FI	Fault intensity	(–)	Q	Air-conditioner capacity	(tons)
FIR	Fault impact ratio	(–)	RT	Runtime	(hours/year)

TMY	Typical meteorological year		
TXV	Thermostatic expansion valve		
UC	Undercharge fault		
V	Value of FDD	($/ton)	
VL	Compressor valve leakage fault		
α	Equipment wear multiplier	(–)	
β	Net benefit of service	($/ton)	
ϕ	fault type		
θ	FDD tool		
ρ	Rate	($/hour)	
τ	Time span for analysis	(years)	

Subscripts

amb	Ambient
b	Bin
E	Energy
f	Faulted
min	Minimum
nom	Nominal
ND	No Diagnosis
NR	No Response
R	Equipment replacement
S	Service
T	Total
u	Unfaulted

REFERENCES

Bonvini, M., M.D. Sohn, J. Granderson, M. Wetter and M.A. Piette, 2014. Robust on-line fault detection diagnosis for HVAC components based on nonlinear state estimation techniques. *Applied Energy* 124(2014): 156-166.

Cheung, H. and Braun, J.E., 2013a, Simulation of Fault Impacts for Vapor Compression Systems by Inverse Modeling Part I: Component Modeling and Validation, *HVAC&R Research*, 19(7): 892-906.

Cheung, H. and Braun, J.E., 2013b, Simulation of Fault Impacts for Vapor Compression Systems by Inverse Modeling Part I: System Modeling and Validation, *HVAC&R Research*, 19(7): 907-921.

Cho, J.M., J. Heo, W.V. Payne and P.A. Domanski. 2014. Normalized performance parameters for a residential heat pump in the cooling mode with single faults imposed. *Applied Thermal Engineering* 67(2014): 1-15.

Du, Z, P.A. Domanski and W.V. Payne. 2016. Effect of common faults on the performance of different types of vapor compression systems. *Applied Thermal Engineering* 98(2016): 61-72.

Li, H. and J.E. Braun. 2007. An overall performance index for characterizing the economic impact of faults in direct expansion cooling equipment. *Int. J. of Refrigeration*, 30 (2007): 299-310.

Mulumba, T., A. Afshari, K. Yan, W. Shen and LK. Norford. 2015. Robust model-based fault diagnosis for air handling units. *Energy and Buildings* 86(2015): 698–707.

Wiggins, M. and J. Brodrick. 2012. HVAC Fault Detection. *ASHRAE Journal* 54(2): 78-80.

Xiao, F., Y. Zhao, J. Wen and S.W. Wang. 2014. Bayesian network based FDD strategy for variable air volume terminals. *Automation in Construction* 41 (2014): 106–118.

Yuill, D.P., H. Cheung and J.E. Braun. 2014a. Evaluation of Fault Detection and Diagnostics Tools by Simulation Results of Multiple Vapor Compression Systems. *Proceedings of 15th International Refrigeration and Air Conditioning Conference*, Paper 2605, West Lafayette, July 2014.

Yuill, D.P., H. Cheung and J.E. Braun. 2014b. Validation of a Fault-Modeling Equipped Vapor Compression System Model Using a Fault Detection and Diagnostics Evaluation Tool. *Proceedings of 15th International Refrigeration and Air Conditioning Conference*, Paper 2606, West Lafayette, July 2014.

Yuill, D.P. and J.E. Braun. 2012. Evaluating Fault Detection and Diagnostics Protocols Applied to Air-cooled Vapor Compression Air-conditioners, Paper 2470 – Revised July 23, *Proceedings of the 14th International Refrigeration and Air Conditioning Conference*, July 16-19.

Yuill, D.P. and Braun, J.E., 2013. Evaluating the performance of FDD protocols applied to air-cooled unitary air-conditioning equipment. *HVAC&R Research*, 19(7): 882-891.

Yuill, D.P. and J.E. Braun. 2016a. Effect of the distribution of faults and operating conditions on AFDD performance evaluations. *Applied Thermal Engineering*, 106 (2016): 1329-1336.

Yuill, D.P. and J.E. Braun. 2016b. A figure of merit for overall performance and value of AFDD tools. *In review*.

ACKNOWLEDGEMENTS

This work was supported by the National Institute of Standards and Technology (NIST). We gratefully acknowledge project oversight by Drs. Piotr Domanski and Vance Payne of NIST.