Explainable AI for Chiller Fault-Detection Systems: Gaining Trust and Human Connect

Seshadhri Srinivasan
Controls and Optimization
GE Research Center, Bangalore, India
email:seshadhri.srinivasan@ge.com

Pandarasamy Arjunan
Berkeley Education Alliance for Research in Singapore, Singapore
email: samy@bears-berkeley.sg

Baihong Jin
Department of Electrical Engineering and Computer Science
University of California, Berkeley
email: bjin@berkeley.edu

Alberto Sangiovanni-Vincentelli
Department of Electrical Engineering and Computer Science
University of California, Berkeley
email:alberto@berkeley.edu

Zuraimi Sultan
Berkeley Education Alliance for Research in Singapore, Singapore
email: zuraimi.sultan@bears-berkeley.sg

Kameshwar Poolla
Department of Mechanical Engineering
University of California, Berkeley
email: poolla@berkeley.edu

***Abstract*—Chillers are energy-intensive, prone-to-faults components used for space cooling in buildings. Data-driven Fault Detection and Diagnosis (DD-FDD) are widely used for chillers. However, field personnel are often not confident in DD-FDD mainly because no explanation is given for the results. EXplainable Artificial Intelligence (XAI) can help bridge this gap. We investigate XAI-FDD's role in building trust in DD-FDD. We examine use-cases for XAI-FDD on a building in Singapore having 6 chillers.**

■ **CHILLER FAULT DIAGNOSIS** Heating, ventilation and air-conditioning (HVAC) systems are used for space cooling in buildings and constitute a significant proportion of the total energy consumption [1]. In countries with tropical climate (e.g., Singapore), the energy consumption by HVAC is around 60% of the total and is likely to grow in the future. Within the HVAC system, the chillers are the most energy-intensive components and their reliable operation is essential for avoiding energy losses, costly maintenance operations, and reducing equipment downtime. Furthermore, HVAC performance is closely linked to occupant comfort and indoor air quality as well [2]. A poorly maintained chiller could decrease occupant well-being and create health issues (e.g., sick building syndrome). To increase chiller reliability and performance, fault-detection and diagnosis (FDD) systems are used [3]. Existing FDD techniques in chillers can be broadly classified as: *i) model-based, ii) data-driven*, and *iii) hybrid* [4]. *Model-based* FDD uses physical laws to capture the component dynamics followed by signal processing operations to determine the presence of faults [5]. However, high-fidelity models are difficult to obtain limiting their applicability. The proliferation of the Internet of Things (IoT) and edge computing is making it possible aggregating and processing a large amount of data. Leveraging these capabilities, *data-driven* techniques are becoming popular for chiller FDD design [6]. These methods typically use raw-data collected from chillers and use Machine Learning (ML) models that perform prediction, classification, regression and pattern recognition to identify faults. Data-driven methods have found significant traction in industry due to their short development time, ability to leverage data and to handle diverse data streams such as images and texts [7]. *Hybrid* approaches combine the two methods. They perform well, but their complexity is high [8].

While data-driven FDD (DD-FDD) methods are being embraced in industry, there is a problem brewing under the surface: field personnel are not comfortable with a process that is not entirely transparent. Indeed, data-driven models are mostly "black box" and the user has no visibility of the logic behind the decisions based on these models [9]. Field technicians' expertise is precious and their involvement in the decision process is necessary. Lack of transparency generates mistrust that may lead to the rejection of data-driven technology in building management. Since building system complexity is growing rapidly, humans without the aid of analytic tools would be facing an almost impossible task. DD-FDD can be run real-time thus providing the opportunity to optimize building operations and in particular, to identify situations where failure may occur, thus allowing preventive maintenance to avoid down-times and inefficient behavior. This situation clearly points to the need of a man-machine collaboration that cannot be but based on data-driven techniques that abandon opacity in favor of more transparency: Explainable Artificial Intelligence.

Explainable Artificial Intelligence

Without model explainability and interpretability, it is hard to engage field personnel and other stakeholders in the decision-making process including proactive maintenance schedules. Several approaches have been proposed for studying model explainability; among them, eXplainable AI (XAI) has emerged as a strong candidate [10], [11]. XAI has received considerable interest in medicine [12], industrial automation [13], and buildings [14], [15], among others. We believe that XAI can play a fundamental role in chiller FDD allowing to overcome model opaqueness and gaining field personnel's trust.

In general, XAI is an AI framework where the rationale/business logic of a model is explained in user-centric terms. This logic helps model transparency by providing records on factors and associations with a given prediction. However, as the model complexity grows the technical challenge of explaining AI model's decision remain severe, yielding the so called *interpretability problem* [16]. There are several approaches that attempt at making ML models and algorithms understand the context and the environment better, and build explanatory models about their own behavior. To underline the importance of this work, the third-gen AI DARPA program is focused on XAI. In this program, the available XAI approaches are broadly classified as follows [17]:

(i) *Deep-explanation* where the objective is to learn explainable structures (e.g., layer-wise relevance propagation);

(ii) *Interpretable models* where the objective is to learn more structured and interpretable causal

models that could be applied to statistical models (e.g., Markov chains);

(iii) *Model induction* where the objective is to infer an interpretable model from a black box one. These models aim to explain the user the AI model's rationale in the close vicinity of a data-instance (local interpretability).

A central role in XAI is played by the Local Interpretable Model-agnostic Explanations (LIME) [18] tool that provides explanations on a single data-instance without depending on specific ML models. More precisely, the *explanation* generated by LIME for data instance x is defined as:

$$\text{explanation}(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g) \quad (1)$$

where $f()$ is the original model, $g()$ is the local explanation for instance x that minimizes the loss function L that measures the fidelity between $f()$ and $g()$, while keeping the model complexity $\omega(g)$ low. π_{x_*} denotes a neighborhood of $\underline{x}_*$ in which approximation is sought. $g()$ belongs to a class of interpretable models, $\mathcal{G}$, such as linear models or decision trees [18]. LIME is an example of *sparse explainer* that is suitable for interpreting machine learning models with a large number of predictors. The important idea behind LIME is to train a local surrogate, interpretable model that approximates the predictions of the underlying black-box model. Since LIME is a readily available off-the-shelf tool, we decided to use it in our experiments.

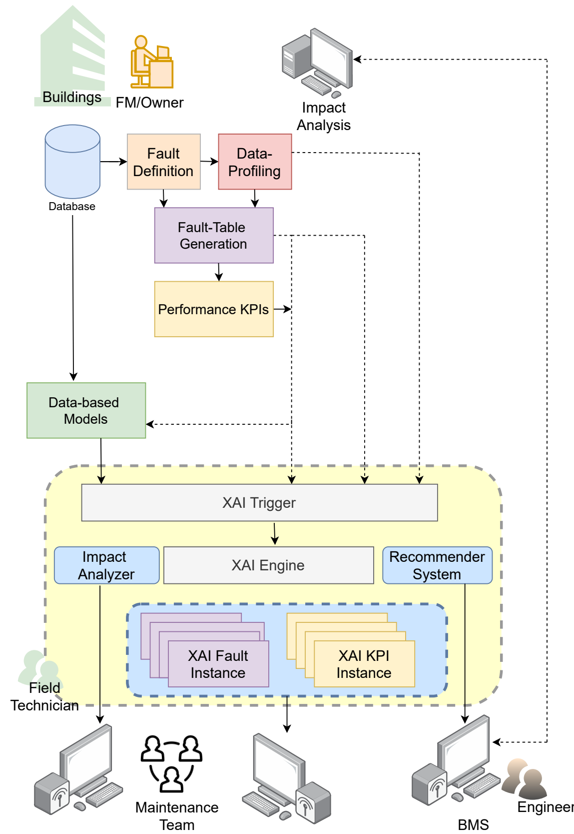

Figure 1: Schematic of XAI-FDD for chillers

XAI-FDD Systems for Chillers

The LIME-based XAI augments DD-FDD methods by deriving explainable approximations of the behavior of the DD-FDD methods around specific data instances. The XAI-FDD schematic is shown in Figure 1. The XAI-FDD workflow starts with collecting labeled data on chiller faults that are stored to a database. Then, the rules for identifying fault conditions are defined and a fault code protocol is established whose syntax has four components: i) fault- level (component or system level), ii) location (e.g., condenser), iii) condition (low/high), and iv) tags (the phenomena that are responsible for the fault). The fault influence on the system (e.g., EN- denotes energy, EFF - efficiency) is also used as fault characterization in addition to the previous four components.

Using the fault-protocol and syntax, a fault-rule is generated that performs data-profiling for each fault that is entered in the fault-table. This table contains data required for understanding faults, rules, conditions, and other aspects specific to faults. For example, Low Chiller Efficiency is defined with CH_LOW_EFF as fault code, data points required are: chiller flow, chiller supply and return water temperature, chiller COP, KW consumption, outside air temperature, chiller status (ON/OFF), % full load ampere, and outside air temperature. The rule that could be used to detect the fault is KW/RT (kilowatt per refrigerant tonnage) ≥ 0.60. These factors are detailed in the fault-table.

Five different key performance indicators (KPIs) are proposed for assessing chiller performance: *(i)* Difference in temperature between the supply and return water in the chiller ($\Delta T_{chiller}$), *(ii)* Difference in temperature between the supply and return water in the condenser ($\Delta T_{condenser}$), *(iii)* Ratio of $DeltaT = \frac{DeltaT_{chiller}}{\Delta T_{condenser}}$, *(iv)* Approach temperature of the cooling tower, *(v)* ratio of $\frac{kW}{RT}$, where kW denotes the electric power consumed by the chiller, RT the refrigerant tonnage and approach temperature is defined as the difference between leaving chilled water temperature and saturated refrigerant evaporating temperature.

The data-driven model uses ML for performing regression or classification to identify faults. We use Extreme Gradient boosting (XGBoost) [19] that consists an ensemble of classification and regression trees. Note that our LIME-based XAI is model agnostic, i.e., XAI just explains the rationale of the model's decision. However, other XAI frameworks may not be model agnostic. For these, model selection should be considered as well.

XGBoost once trained on the labeled chiller data, predicts whether a given sample represents a healthy/faulty operating condition using multi-class classification. The KPIs are computed in real-time. Whenever they exceed a certain threshold value (e.g., $\frac{kW}{RT} < 0.6$), LIME explanations are triggered. The data instance requiring explanations is then transferred from the data-profiling service to the XAI engine. Within the XAI engine, there are two *explainers* for local samples: they are the XAI fault instance and the XAI KPI instance. These instances explain why a particular sample was classified to be a fault and/or how the KPIs are impacted by the fault. In addition, there is an impact analyzer that has analytical models to compute the fault impacts on performance. The "recommender" is a dialogue system that displays variable thresholds causing a fault and estimations on possible locations. Our XAI-based FDD offers explanations to the field personnel, with significant insights into the rationale used to decide whether a state is a fault.

XAI advantages

Since our approach to XAI-FDD is based on the application of ML FDD models, our analysis is based on the value that XAI adds to DD-FDD. We examine incipient and developing faults. We will underline the advantages also in the use-case section.

Incipient faults are more frequent and hard to perceive from noise as their fault signatures have lower amplitude and appear for shorter time. XAI-FDD helps detecting incipient faults as explanations are generated for a particular sample. By "explaining" a single data-instance (local explanations), XAI provides valuable information to classify the data instance as incipient fault by possibly resorting to human support. Hence, this approach may detect faults earlier during their occurrence than with DD-FDD methods that may not trigger the correct classification.

As per developing faults, DD-FDD may provide a fault characterization in a form that is difficult for field engineers to understand. With XAI-FDD the fault causes could be easily detected through explanations. Moreover, thresholds based on which the sample was classified as faults are provided.

The additional information and explanation provided by XAI may prevent a fault to reach a degree of severity that causes disruption of services and discomfort for building occupants. Standard DD-FDD may not provide enough confidence in the building managers and field personnel to trigger an appropriate maintenance action.

FDD Workflow and Stakeholder Actions

The workflow and stakeholder actions with DD-FDD and XAI-FDD are shown in Figure2. The fault-cycle with DD-FDD starts with stray alarms: following the alarm, the field technician resets the alarms and plans maintenance actions. The next stage is declaration of a minor fault that the field technician escalates to the field engineer who advises maintenance/replacement actions. Based on these fault declarations, the field engineer evolves maintenance plans. Finally, the field technicians perform repairing/replacement of parts based on the field engineer inputs. The field engineer could escalate this to the building owner or facility manager for costly replacements and procurement. Consequently, most time in DD-FDD workflow is spent on fault-detection, performing root-cause analysis to escalate actions to the next hierarchical level. This process may take considerable time thus reducing the possibility of catching faults early before they become severe.

The XAI-based FDD workflow and actions are shown on the top. The first phase is the incipient fault declaration from individual data-instances and this helps field technicians to under-

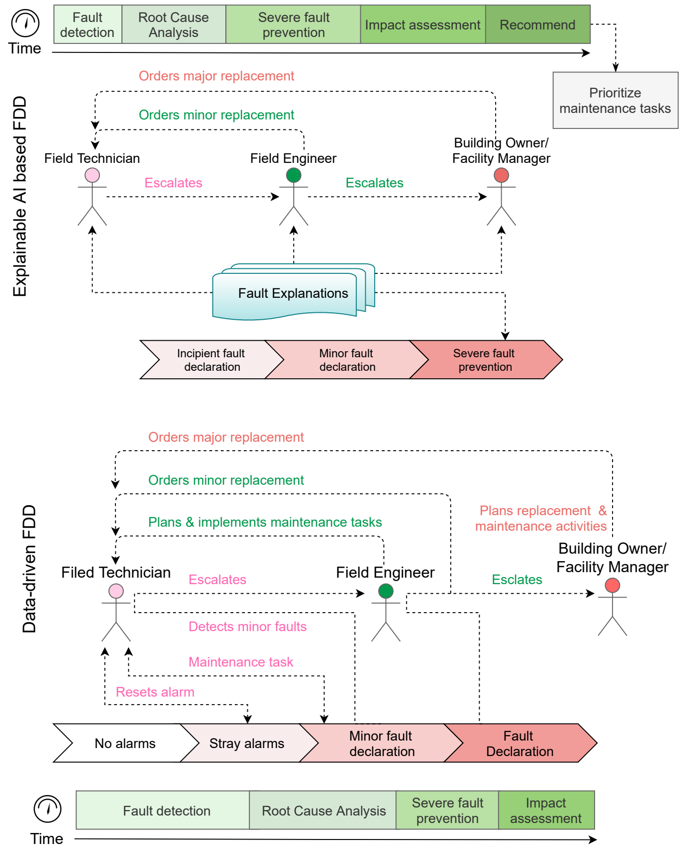

Figure 2: Workflow and stakeholder actions

stand the fault causes that could be used to plan simple maintenance operations. A minor fault declaration happens well-ahead in the fault cycle and this triggers corrective actions through pro-active maintenance schedules. Severe faults are almost prevented in case of XAI-FDD methods as fault causes are examined at the incipient stage. Consequently, significant amount of time in XAI-FDD is spent on impacts assessment and severe fault prevention, key aspects to eliminate costly maintenance operations/repairs. In addition, XAI-FDD provides options to perform impact assessment and could also offer recommendations for repairing certain faults.

Use-cases of XAI-FDD

This section demonstrates the value added of XAI-FDD with respect to pure DD-FDD. For our experiments, we collected data from a building in Singapore having 6 chillers of different ratings (650RT, 650RT, 200 RT,380RT, and 600 RT). Chiller fault data were collected from June 1, 2018 to Jan 1, 2020. The system faults, the fault-logs and maintenance logs were used to decorate the faults with the time-stamped data. The following use-cases are considered:

(i) *Incipient faults*: scaling in condenser fins;
(ii) *Sensor errors*: identify sensor errors that are caused by pulsations in flow;
(iii) *False positive*: a faulty condition sample identified as healthy by DD-FDD but overruled by XAI-FDD.

These use-cases are selected for illustrative purpose only. An exhaustive discussion on use-cases is outside the scope of the paper. However, our XAI methodology could be applied to any type of faults foreseen in a chiller system. In the Figures below, explanations are obtained using the XAI engine, while the prediction probabilities provided as percentages in the plot, are derived using XGBoost.

Incipient Fault Detection

This use-case addresses incipient fault detection using XAI. The incipient faults are intermittent and appear for a short time; consequently, the signals are hard to perceive. XAI could be used to detect incipient faults from analysis of explanations time history. Explanations on two different samples within a short time-frame of 25 min are shown in Figure 3(a), and (b), respectively. The incipient fault analyzed here is caused by the beginning of condenser fouling. In Figure 3(a) and (b), the red bars show possible fault causes along with the threshold values of the variables that indicates the likelihood that a fault is indeed present due to this cause and the blue bars are associated to potential fault causes that are still in the range of normal behavior. The length of the bars also points to the weighted contributions of the variables towards declaring a particular sample to be a fault or healthy condition. At this time instant, CDW_DT, a key KPI, is below the limit of normal behavior while the chiller water temperature difference is within the limits of normal behavior. Considering these values, XAI interprets that with high probability, the chiller to be healthy (82.6%). Figure 3 (b) refers to the values of the KPIs after 25 minutes. Here, even though the chiller flow is still high (> 2.49), the fault probability is increased dramatically to 99.8% because in addition to CDW_DT being below threshold, the difference between the condenser supply water and return water temperature has decreased significantly, a sign of a condenser fault. The field engineers can then declare the real presence of the fault after examining the XAI report and take appropriate actions.

Sensor Faults

Sensor faults are common but difficult to catch at individual samples. In this use-case, the sensor values of the chiller return water CHW_FLOW are incorrect due to sensor calibration malfunctioning. In general, the sensor reading in Figure 4 (CHW_FLOW ≤ 0.11) indicates a pump fault or severe pulsation in the flow. This condition raises an alarm in the Building Management System requiring the field personnel to either reset the sensor in case they decide that it was a false alarm, or do a site visit at the pump location. However, their decision is based on experience

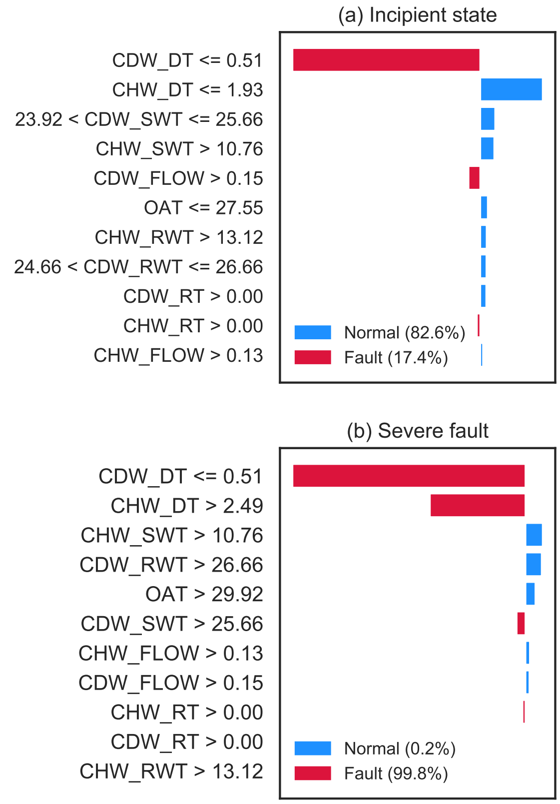

Figure 3: LIME explanation for incipient at (a) starting state and (b) incipient fault state

since they do not have a complete explanation of the faulty behavior.

XAI can come to the rescue in this situation as shown in Figure 4. The sample is declared a healthy sample, but with an anomaly, i.e., the difference between the chiller supply and return water temperature (CHW_DT ≥ 2.49). On the other hand, chiller RT (CHW_RT), chiller supply water temperature (CHW_SWT), and chiller return water temperature (CHW_RWT) all are typical of a healthy condition. Presented with these explanations, the field personnel may conclude that a sensor fault has occurred and take appropriate actions before severe damage to the sensing system develops.

False Positives

In this use-case, the sample considered in Figure 5 has been identified by DD-FDD a faulty operating state given that the condenser supply and return water difference is very small, and that the condenser return-water temperature is very

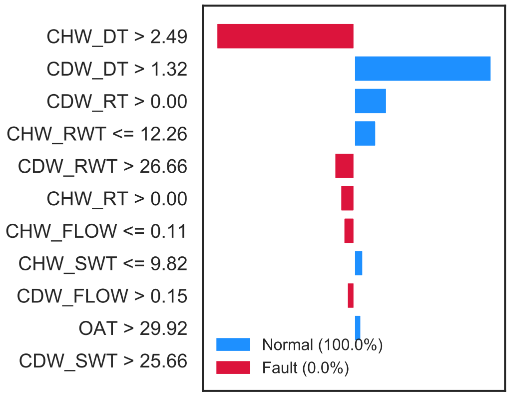

Figure 4: LIME explanation for sensor fault.

low pointing to a fault in the condenser or cooling tower.

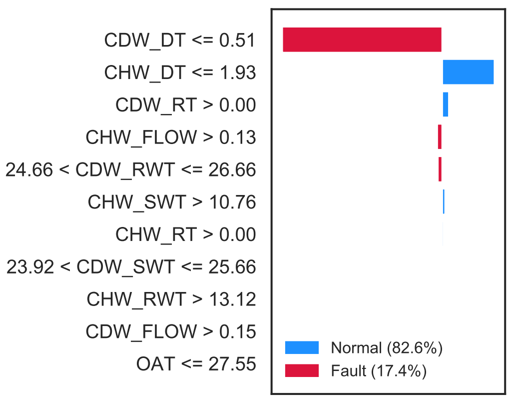

Figure 5: LIME explanation for false positive.

However, XGBoost classified it as a healthy condition with high confidence (82.6%) since the chiller temperature difference is in the normal operation range. XAI-FDD triggered a complete explanation on the KPI being violated and the other conditions that are within limits presenting the field personnel a rich set of information that can be used to decide whether the case is a false alarm.

Inputs to Field Personnel

In the use-cases above, the correctness of the recommendations of DD-FDD on the presence or absence of faults is difficult to ascertain for the field personnel. In particular, incipient faults are not detectable without human inspection dismantling the condenser. We showed in use-case (i), XAI-FDD provides explanations that can be easily understood by the field personnel to take actions. Similarly, in use-case (ii), we showed that a sensor error is very hard to capture. This type of faults can generate continuous alarms that can propagate to other parts of the system. XAI-FDD can provide enough explanations to identify these faults where other methods would not offer the appropriate information. False alarms are a major problem with DD-FDD; however, use-case (iii) shows that using XAI-FDD, the field personnel could understand whether a false alarm has been triggered. We postulate that XAI-FDD may become the user interface of choice for field personnel in lieu of a Building Management System as it is today because of the wealth of information that can be used to aid maintenance planning as well as troubleshooting.

CONCLUSIONS AND FUTURE DIRECTIONS

A workflow for the development of eXplainable Artificial Intelligence-based fault detection and diagnosis system (XAI-FDD) for chillers was proposed. XAI-FDD reduces fault-detection time, performing root-cause analysis, and helps planning maintenance operations. This reduces actual faults and improves the accuracy of fault-impact assessment. For building operations, XAI-FDD helps increasing the field personnel trust on FDD methods. Furthermore, XAI-FDD could be used as the user interface of choice for field personnel to troubleshoot faults, detect incipient faults, and plan maintenance operations. The benefits of XAI-FDD were illustrated on a high-performance building through a number of use-cases. The results demonstrate the value proposition and the ability of the system to reduce the digital divide between field personnel and the FDD systems. The XAI-FDD framework can be extended to renewable energy sources, air-handling units, and other energy components in a building. Future work will include XAI-FDD implementation on edge devices and the study of how to optimize the use of XAI-FDD by field engineers/technicians.

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REFERENCES

1. N. Radhakrishnan, S. Srinivasan, R. Su, and K. Poolla, "Learning-based hierarchical distributed hvac scheduling with operational constraints," *IEEE Transactions on Control Systems Technology*, vol. 26, no. 5, pp. 1892–1900, 2017.
2. S. Atthajariyakul and T. Leephakpreeda, "Real-time determination of optimal indoor-air condition for thermal comfort, air quality and efficient energy usage," *Energy and Buildings*, vol. 36, no. 7, pp. 720–733, 2004.
3. B. Su and S. Wang, "An agent-based distributed real-time optimal control strategy for building hvac systems for applications in the context of future iot-based smart sensor networks," *Applied Energy*, vol. 274, p. 115322, 2020.
4. A. Beghi, L. Cecchinato, F. Peterle, M. Rampazzo, and F. Simmini, "Model-based fault detection and diagnosis for centrifugal chillers," in *2016 3rd Conference on Control and Fault-Tolerant Systems (SysTol)*. IEEE, 2016, pp. 158–163.
5. F. Acerbi and G. De Nicolao, "Identification of the gordonng chiller model: Linear or nonlinear least squares?" in *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, vol. 1. IEEE, 2018, pp. 1314–1321.
6. B. Wu, W. Cai, and X. Zhang, "A fault detection model for air handling units based on the machine learning algorithms," in *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2020, pp. 4789–4793.
7. B. Jin, Y. Tan, A. Liu, X. Yue, Y. Chen, and A. S. Vincentelli, "Using ensemble classifiers to detect incipient anomalies," *arXiv preprint arXiv:2008.08710*, 2020.
8. K. Yan, W. Shen, T. Mulumba, and A. Afshari, "Arx model based fault detection and diagnosis for chillers using support vector machines," *Energy and Buildings*, vol. 81, pp. 287–295, 2014.
9. H. Han, X. Cui, Y. Fan, and H. Qing, "Least squares support vector machine (ls-svm)-based chiller fault diagnosis using fault indicative features," *Applied Thermal Engineering*, vol. 154, pp. 540–547, 2019.
10. R. Confalonieri, L. Coba, B. Wagner, and T. R. Besold, "A historical perspective of explainable artificial intelligence," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, p. e1391, 2020.
11. H. Hagras, "Toward human-understandable, explainable ai," *Computer*, vol. 51, no. 9, pp. 28–36, 2018.
12. A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence (xai)," *IEEE Access*, vol. 6, pp. 52 138–52 160, 2018.
13. K. Gade, S. C. Geyik, K. Kenthapadi, V. Mithal, and A. Taly, "Explainable ai in industry: practical challenges and lessons learned: implications tutorial," in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 2020, pp. 699–699.
14. M. Madhikermi, A. K. Malhi, and K. Främling, "Explainable artificial intelligence based heat recycler fault detection in air handling unit," in *International Workshop on Explainable, Transparent Autonomous Agents and Multi-Agent Systems*. Springer, 2019, pp. 110–125.
15. P. Arjunan, K. Poolla, and C. Miller, "Energystar++: Towards more accurate and explanatory building energy benchmarking," *Applied Energy*, vol. 276, p. 115413, 2020.
16. E. Tjoa and C. Guan, "A survey on explainable artificial intelligence (xai): Toward medical xai," *IEEE Transactions on Neural Networks and Learning Systems*, 2020.
17. M. Ribera and A. Lapedriza, "Can we do better explanations? a proposal of user-centered explainable ai." in *IUI Workshops*, 2019.
18. M. T. Ribeiro, S. Singh, and C. Guestrin, "" why should i trust you?" explaining the predictions of any classifier," in *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 1135–1144.
19. T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data mining*, 2016, pp. 785–794.

Seshadhri Srinivasan (Sr.Member, IEEE) is currently working as Lead Scientist with GE Research Center (Controls and Optimization), Bangalore, India. Prior to joining GE, he was working with the Berkeley Education Alliance for Research in Singapore (BEARS), Singapore from 2015-2020. Prior to joining BEARS, he was with the University of Sannio, Italy, Technical University of Munich, Germany, Tallinn University of Technology, Estonia, and ABB Corporate Research Center at Bangalore. He is a member of

the IEEE CSS standing committee on standards.

Pandarasamy Arjunan is currently with the Berkeley Education Alliance for Research in Singapore working on energy benchmarking, city-scale analytics, and fault detection and diagnosis for smart buildings. He has received his Ph.D. degree in computer science and engineering from Indraprastha Institute of Information Technology Delhi (IIIT-Delhi), India. He is a student member of IEEE.

Baihong Jin received the B.S. degree in microelectronics from Peking University, Beijing, China. He has received his Ph.D. degree in electrical engineering and computer sciences at the University of California Berkeley, Berkeley, CA, USA. He is interested in developing data-driven techniques for analyzing cyber–physical systems, with a particular focus on the fault detection, diagnosis, and prognosis for smart building systems.

Alberto Sangiovanni-Vincentelli (Fellow, IEEE) is the Edgar L. and Harold H. Buttner Chair at the Department of Electrical Engineering and Computer Science, University of California, Berkeley, CA, USA, where he has been a member of the faculty since 1976. He is a Fellow of the Association for Computing Machinery (ACM), a member of the National Academy of Engineering, and holds two honorary Doctorates from Aalborg University (Denmark) and KTH (Sweden). He co-founded Cadence and Synopsys, the two leading EDA companies.

He earned the IEEE/RSE Maxwell Medal for groundbreaking contributions that have had an exceptional impact on the development of electronics and electrical engineering, the Kaufmann Award for seminal contributions to EDA, the EDAA lifetime Achievement Award, the IEEE/ACM R. Newton Impact Award, the University of California Distinguished Teaching Award, the IEEE Technical Committee on Cyber-Physical Systems (TC-CPS) Technical Achievement Award for pioneering contributions and leadership in cyber-physical systems and design automation, the International Symposium on Physical Design (ISPD) lifetime achievement award, intended for individuals who have made outstanding contributions to the field of physical design automation over multiple decades and the IEEE Graduate Teaching Award for inspirational teaching of graduate students. He authored over 950 papers, 19 books, and two patents.

Zuraimi Sultan is the Program Director of SinBerBEST Program at the Berkeley Education Alliance for Research in Singapore. He received his Ph.D. in Building Science from the Department of Building, School of Design and Environment, National University of Singapore.

Kameshwar Poolla is the Cadence Design Systems Distinguished Professor, in Department of Electrical Engineering and Computer Sciences and Department of Mechanical Engineering at University of California, Berkeley. He received his B.Tech. degree from the Indian Institute of Technology, Bombay in 1980 and his Ph.D. from the Center for Mathematical System Theory, University of Florida, Gainesville in 1984. Poolla's research interests include many aspects of future energy systems including economics, security, and commercialization. He was awarded the 1984 Outstanding Dissertation Award by the University of Florida; the 1988 NSF Presidential Young Investigator Award; the 1993 Hugo Schuck Best Paper Prize; the 1994 Donald P. Eckman Award; a 1997 JSPS Fellowship; the 1997 Distinguished Teaching Award from the University of California, Berkeley; and the 2004 and 2007 IEEE Transactions on Semiconductor Manufacturing Best Paper Prizes; and the 2009 IEEE CSS Transition to Practice Award.