Knowledge-based vs. Data-driven? Fault Detection and Diagnosis in Buildings

Dr. Chujie Lu

Postdoctoral Researcher

Dept. of AE+T, TU Delft

c.j.lu@tudelft.nl

TU Delft Department of Architectural Engineering +Technology

BK Bouwkunde

Overview

- **Background**: Fault Detection and Diagnosis (FDD) in Buildings
- **Data-driven FDD**: Critical Case Analysis
- **Diagnostic Bayesian Network (DBN)**
- **Ongoing research in TUD**

Background: energy use in buildings

- Buildings are the single largest energy consumer in Europe.

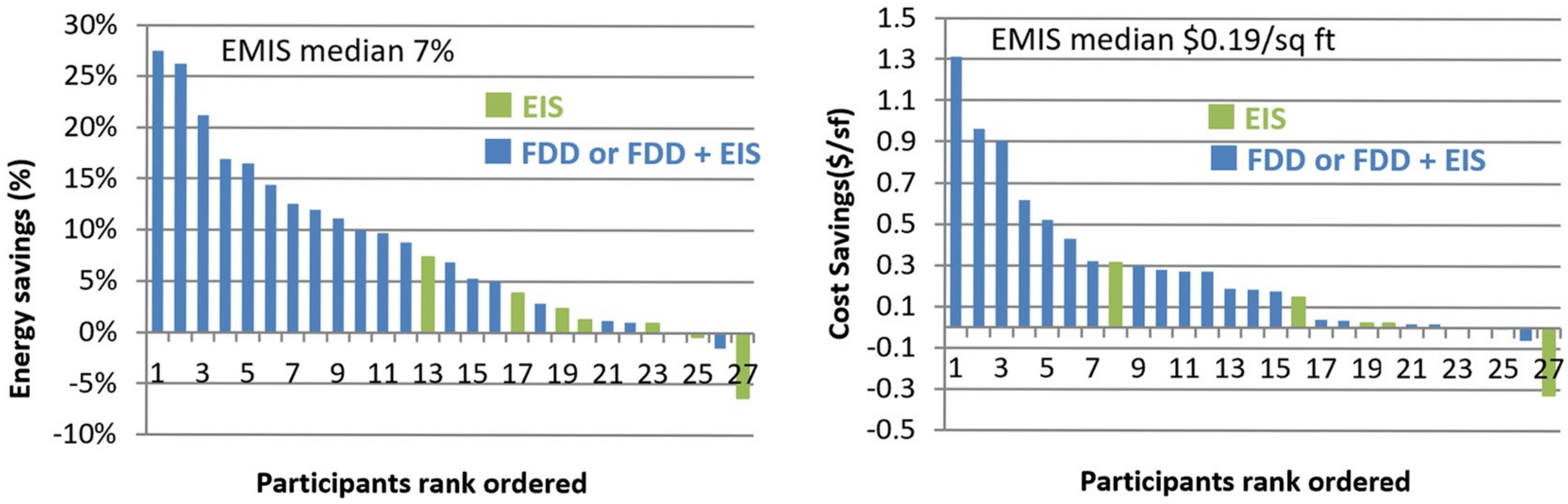
around 40%	over 1/3	+/- 80%
of energy consumed in the EU is used in buildings	of the EU's energy-related GHG emissions come from buildings	of energy used in EU homes is for heating, cooling and hot water

- The revised **Energy Performance of Buildings Directive**: achieve emission reductions of at least 60% in the building sector by 2030 compared to 2015 and to reach climate neutrality by 2050.

➢ Key task: minimizing the energy waste in buildings!

Background: FDD in buildings

- **Why FDD is needed?**
  - A survey on energy and cost savings since the installation of the Energy Information Systems (EIS) and FDD. (LBNL, US)



  - Comfort maintaining! Energy saving! Cost saving!

Background: FDD in buildings

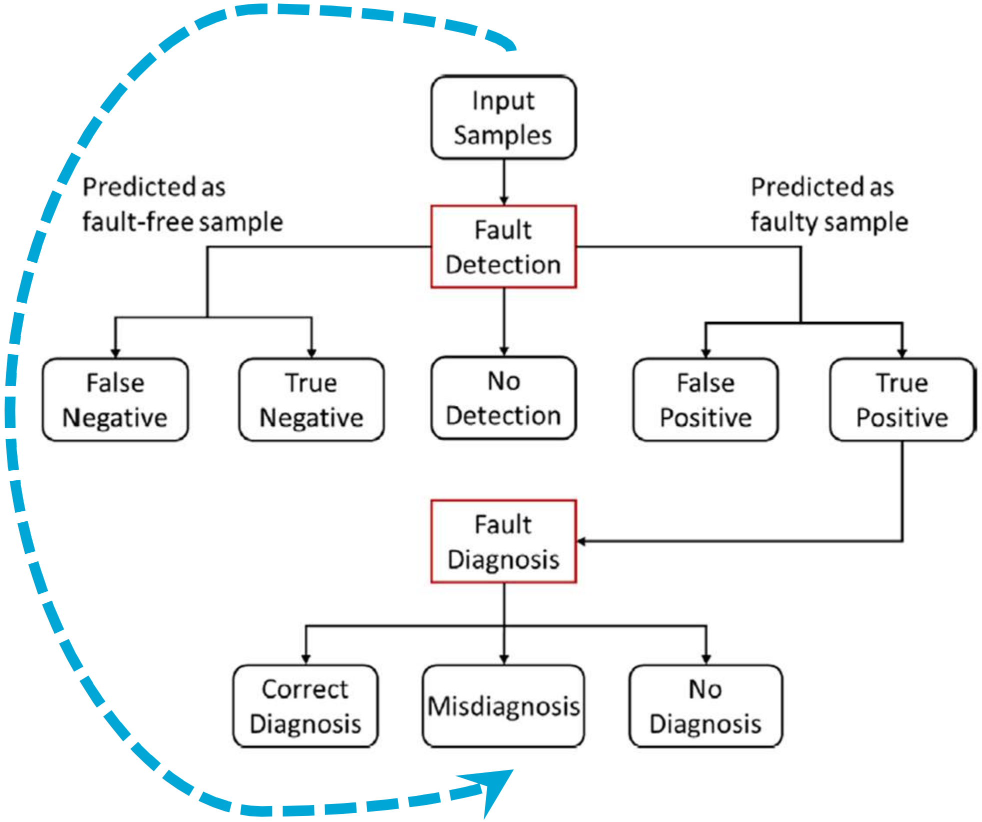
- **What is Fault**?
  - ➢ Condition-based: Improper or undesired *physical conditions* (Stuck valves/Fouled coils/Broken actuators/…)
  - ➢ Behavior-based: Improper or undesired *behaviors* during the operation (Reduced water flow/Reduced supply temp./…)
  - ➢ Outcome-based: Quantifiable outcome or performance metrics deviate the expected outcome (Increased energy use/Reduced COP/Uncomfortable indoor temp./…)

If people feel alright and there is no extra energy waste, would it be a fault?

Frank et al., Energy Build (2019)

Background: FDD in buildings

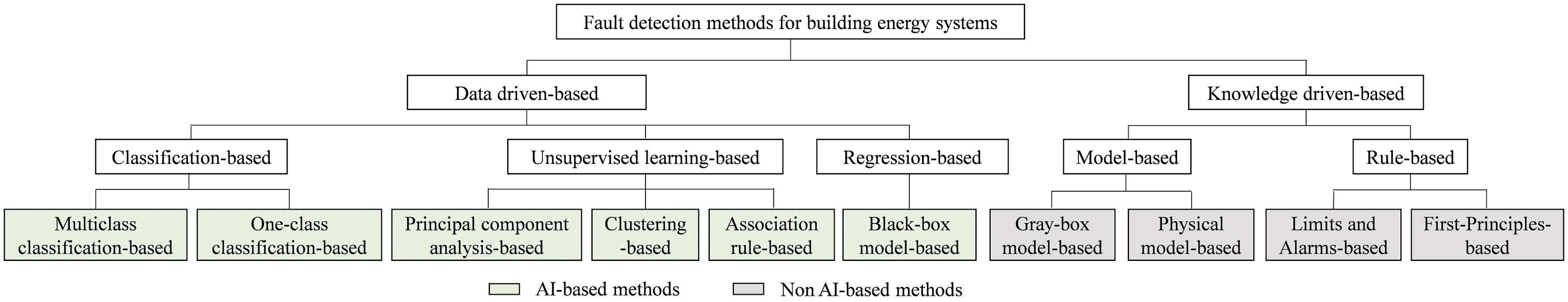
- **What is Fault Detection and Diagnosis?**
  - ➢ Fault Detection: check whether a fault has occurred
  - ➢ Fault Diagnosis/Identification/Isolation: identify the type of a fault and its location
  - ➢ Some FDD methods (Data-driven) can deal with two steps simultaneously



Reddy et al., ASHRAE Trans (2007)

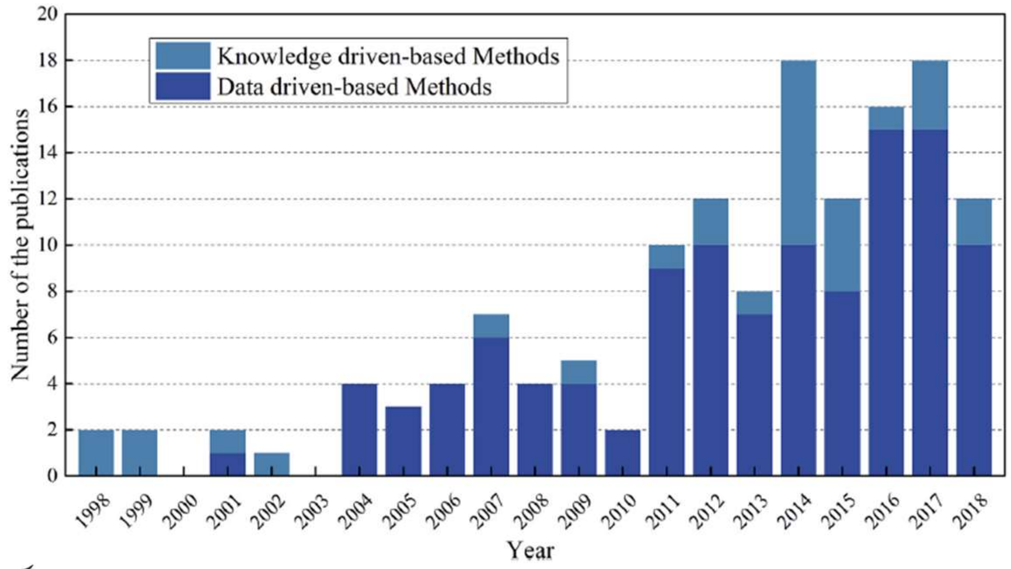
Background: FDD in buildings

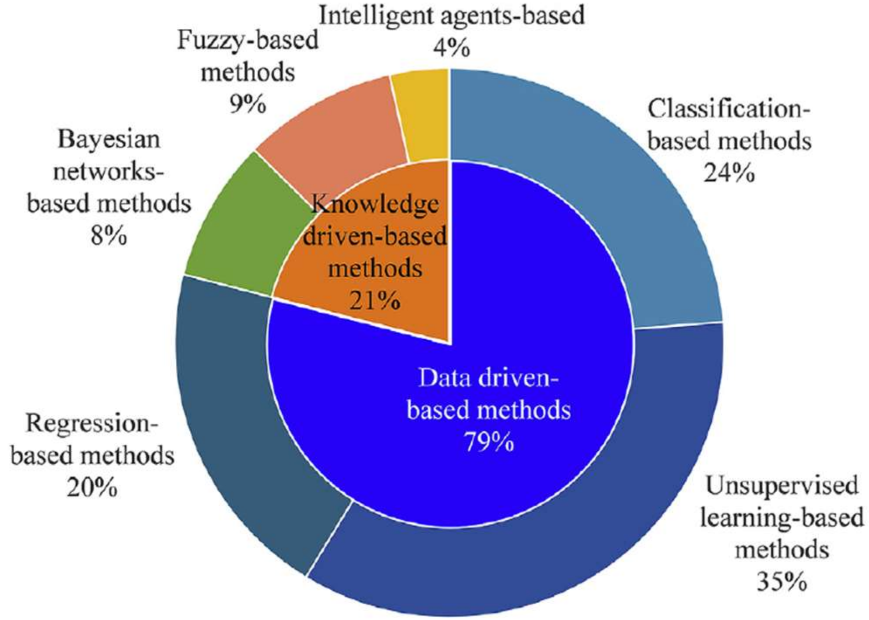
- **How to diagnose Faults?**
  - ➢ Knowledge-based: Diagnosis rely on expert experience and domain knowledge
  - ➢ Data-driven: Fault Pattern “Knowledge” is obtained from data.



Background: FDD in buildings

- **FDD in Academia: A Rising Trend! (With the boom in AI)**
  - In 2023, more than 50 publications
  - Over 70% are data-driven!





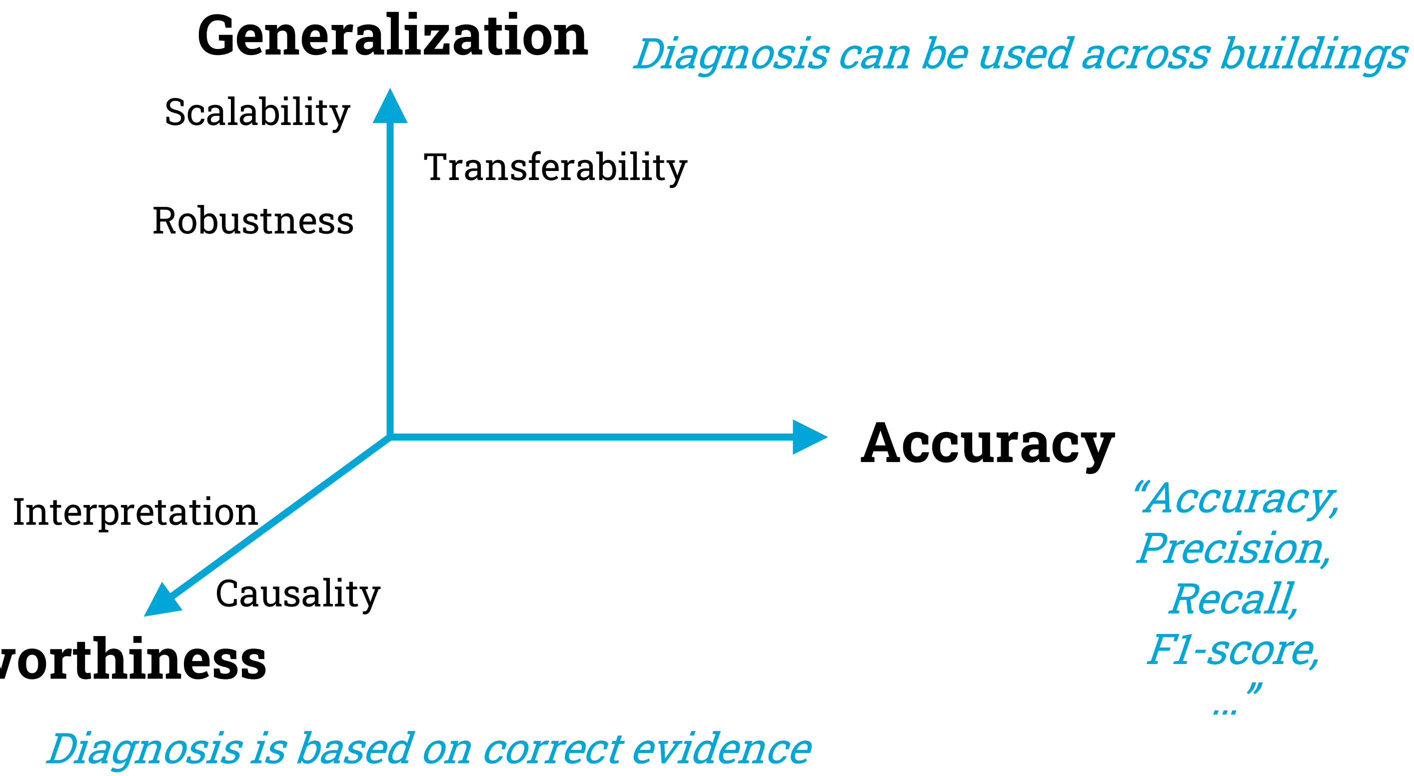
Background: FDD in buildings

- **FDD in Industry: Reluctant?**
  - **Unfamiliar:** FDD seems to be an academic definition, customers rarely knew the benefits of FDD (Aalburg, DK)
  - **Expensive:** FDD base cost was five times higher than the EIS base cost, and the FDD ongoing costs were double that of EIS. (LBNL, US)
  - Lack of a viable business model for FDD
  - ……
- **FDD Methods in Industry: Still knowledge-based !**
  - Expert systems for FDD in HVAC systems are still predominantly used (Aalburg, DK; LBNL, US; CRC, AU)

Disjunction between academia and industry!

Andersen et al., Energy Build (2024)
Kramer et al., Energy Efficiency (2020)
Wall et al., CRC for lower carbon living (2018)

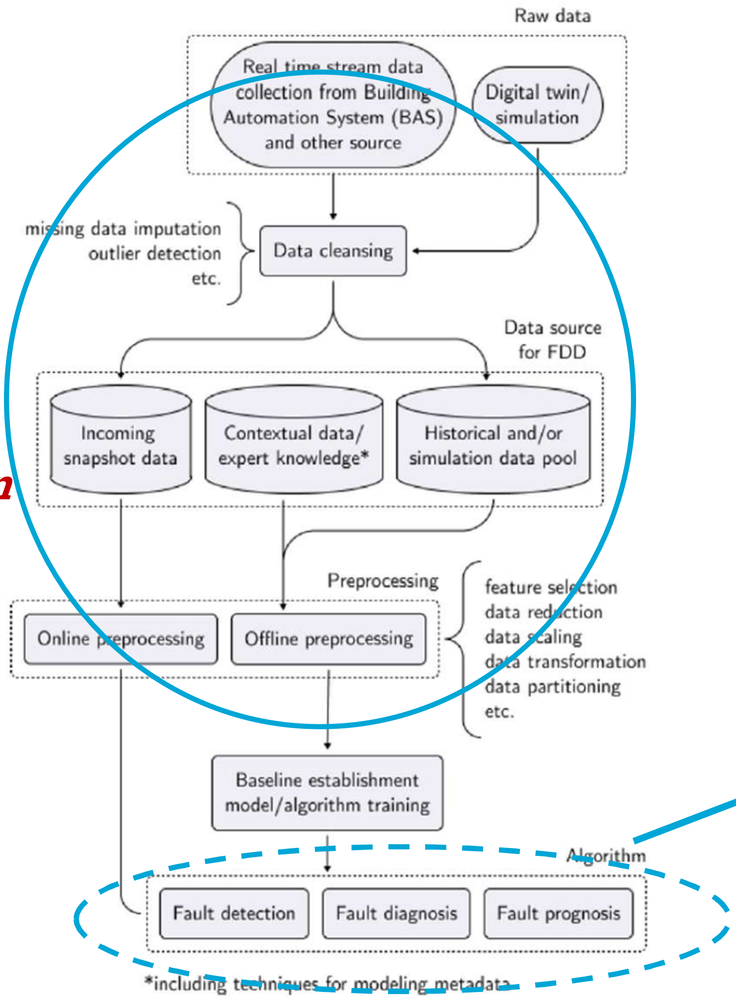
What is a good data-driven model?



Data-driven FDD in Buildings

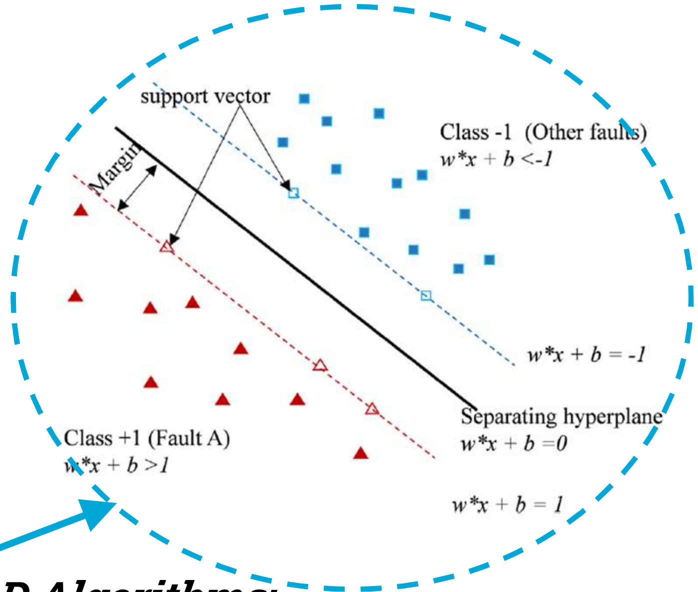
- **General Process**

Data Preparation



High-quality data

"Garbage in, garbage out!"



FDD Algorithms:

SVM classification

Chen et al., Applied Energy (2023)

What is high-quality data for FDD?

- Data from sufficient sensors
  - ➢ Sensor survey on 18 AHUs in the Netherlands

➢ **Building Technical Standards**
ASHRAE (US):
basic requirement for FDD

Sensor	A	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Outdoor air temperature	✓	✓				✓			✓			✓	✓		✓	✓	✓	✓	✓
Outdoor air relative humidity																✓	✓	✓	✓
Preheated air temperature	✓			✓									✓			✓	✓	✓	
Preheated air relative humidity													✓						
Supply air temperature	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
Supply air relative humidity				✓		✓		✓	✓		✓	✓			✓	✓	✓	✓	✓
Return air relative humidity				✓		✓		✓	✓		✓	✓	✓		✓	✓	✓	✓	✓
Exhaust air temperature	✓				✓	✓							✓		✓	✓	✓	✓	✓
Exhaust air relative humidity													✓			✓	✓		
Supply water temperature	✓												✓	✓		✓			
Return water temperature	✓					✓			✓	✓	✓	✓	✓			✓	✓	✓	✓
Pressure difference at supply air filter		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pressure difference at return air filter				✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Pressure difference at supply air on fan				✓							✓					✓			
Pressure difference at return air on fan											✓								
Supply air flow rate	✓		✓													✓			
Return air flow rate	✓																		
Coil valve control signal	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Supply fan control signal	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Return fan control signal	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Supply damper control signal		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Return damper control signal		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Air quality sensor					✓		✓		✓					✓					
Temperature sensor after coil	✓					✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Coil water flow									✓		✓								
Fit ASHRAE recommendation	-												Yes			Yes	Yes	Yes	

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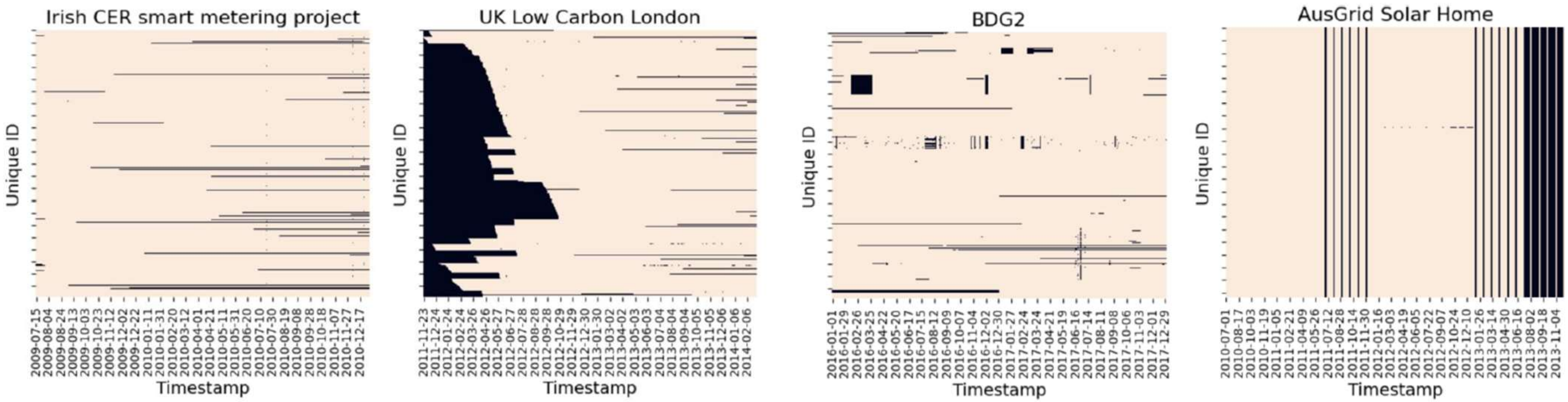
What is high-quality data for FDD?

- Data from sufficient sensors
- Data without missing values



Black spots or streaks are missing data values

What is high-quality data for FDD?

- Data from sufficient sensors
- Data without missing values
- Data with faulty labels
  - ➢ Fault Experiments

WINTER EXPERIMENTS					
Fault LBK201	Fault LBK 202	Start Date	Start Time	Stop Date	Stop Time
Fan Stuck (30%)	Fan Stuck (30%)	2024/3/23	08:21	2024/3/23	11:14
Fan Stuck (70%)	Fan Stuck (70%)	2024/3/23	11:14	2024/3/23	14:32
Heat Recovery Wheel Stuck (0%)	Heat Recovery Wheel Stuck (0%)	2024/3/23	14:32	2024/3/23	17:00
Heat Recovery Wheel Stuck (30%)	Heat Recovery Wheel Stuck (30%)	2024/3/23	17:00	2024/3/23	20:08
Heat Recovery Wheel Stuck (70%)	Heat Recovery Wheel Stuck (70%)	2024/3/24	08:02	2024/3/24	11:05
Incorrect Supply Air Pressure Set Point (+50=235)	Incorrect Supply Air Pressure Set Point (+50)	2024/3/24	11:05	2024/3/24	13:58
Incorrect Supply Air Pressure Set Point (-50=135)	Incorrect Supply Air Pressure Set Point (-50)	2024/3/24	13:58	2024/3/24	17:00
Incorrect Supply Air Pressure Sensor Reading (=130)	Incorrect Supply Air Pressure Sensor Reading (=130)	2024/3/24	17:00	2024/3/24	20:00

What is high-quality data for FDD?

- Data from sufficient sensors
- Data without missing values
- Data with faulty labels
- Data with balanced labels
  - ➢ Fault Frequency

Fault Name	Raw Fault Frequency (across 11,255 AHU work orders over 5 years)
Supply Fan Complete Failure	825
HCV Stuck Open	689
HCV Stuck Closed	505
Supply Fan Efficiency Degradation (20%)	489
Return Fan Complete Failure	473
Return Fan Efficiency Degradation (20%)	452
CCV Stuck Open	428
Heating Coil SAT Negative Bias	315
Heating Coil SAT Positive Bias	315
HCV Stuck Partially Open (50%)	251
CCV Stuck Closed	234
Return Fan Stuck 50	215
Supply Fan Stuck 50	204
HCV Leaky Valve	137
HC Fouling (20%)	120
North Zone RAT Neg. Bias	107
North Zone RAT Pos. Bias	107
South Zone RAT Neg. Bias	107
South Zone RAT Pos. Bias	107
CCV Stuck Partially Open (50%)	89
CCV Leaky Valve (20%)	84
CC Fouling (20%)	53

Srinivasan Gopalan (2023)

What is high-quality data for FDD?

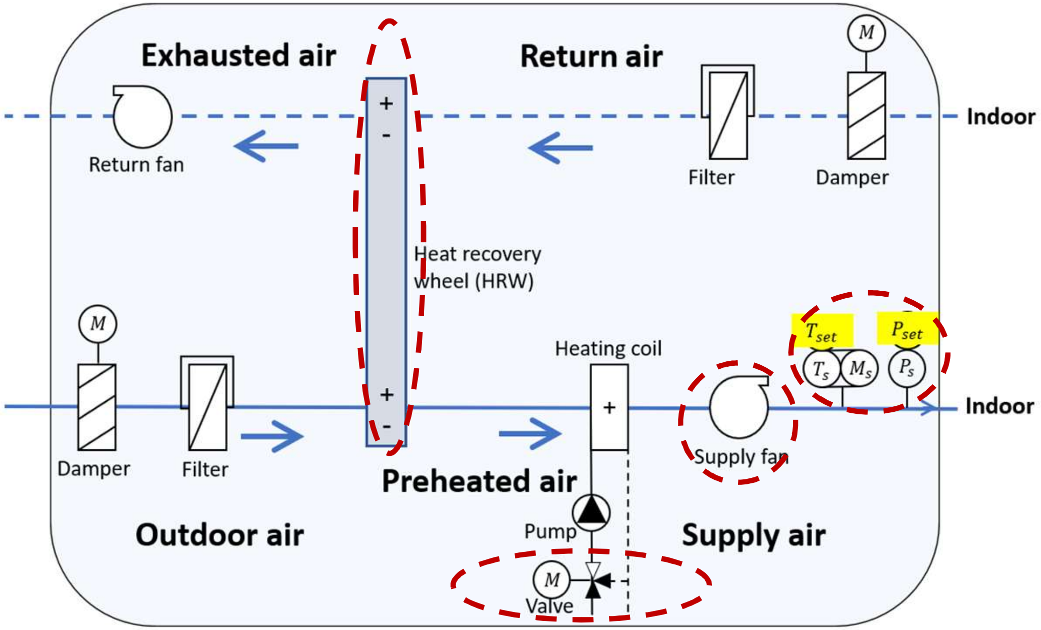
- Data from sufficient sensors
- Data without missing values
- Data with faulty labels
- Data with balanced labels
- Data with generalized (real) distributions
  - ➢ Building energy data can exhibit diverse and complex distributions due to **varying operational conditions, installations, environmental factors, and occupancy.**
  - ➢ Fault experiments are expensive and time-consuming! But **limited experiments cannot reflect faulty data distribution in real buildings**.

Data-driven FDD

- **Air handling Units (AHU) with heat recovery wheel (HRW)**

Data Preparation → Feature Selection → Data Scaling → Model Selection and Training → Evaluation

- ➢ Common system in the context of northern Europe
- ➢ AHU with HRW is highly recommended for safe and healthy ventilation in the post-Covid era



Data-driven FDD

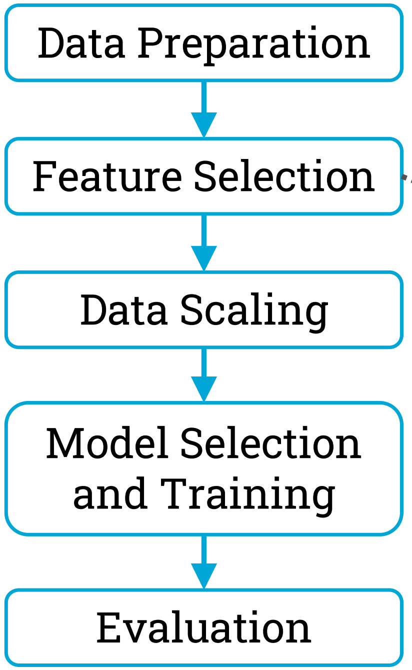
- **Air handling Units with heat recovery wheel**
  - Fault experiments during March 2024
  - In total, 15 faults were conducted
  - Each fault was conducted from 2 to 4 hours. The data interval is 5 minutes

Type	Fault	State	Samples	No.
Component	Fan Stuck	30%	30	F_1
		70%	36	F_2
	Heat Recovery Wheel Stuck	0%	27	F_3
		30%	34	F_4
		70%	35	F_5
	Heating Coil Valve Stuck	0%	22	F_6
		30%	30	F_7
		100%	36	F_8
Control	Incorrect Supply Air Pressure Setpoint	235Pa	31	F_9
		135Pa	36	F_{10}
	Incorrect Supply Air Temp. Setpoint	23°C	38	F_{11}
		17°C	39	F_{12}
Sensor	Incorrect Supply Air Pressure Reading	230Pa	33	F_{13}
		120Pa	33	F_{14}
	Incorrect Supply Air Temp. Reading	17°C	21	F_{15}
Normal	/	/	50	N

B4B Webinar#15 ***Fault Experiments to Generate Data from Living Laboratory*** *(Srinivasan Gopalan, Karzan Mohammed, Jan. 2024)*

Data-driven FDD: Critical Analysis

- **Knowledge-assisted Feature Selection**



No.	Abbr.	Description	Unit
1	T_o	Outdoor air temperature	°C
2	T_p	Preheated air temperature	°C
3	T_s	Supply air temperature	°C
4	T_r	Return air temperature	°C
5	T_e	Exhausted air temperature	°C
6	T_w	Return water temperature	°C
7	H_s	Supply air humidity	%
8	P_s	Supply air static pressure	Pa
9	ΔP_s	Pressure difference at supply air filter	Pa
10	ΔP_r	Pressure difference at return air filter	Pa

Data-driven FDD: Critical Analysis

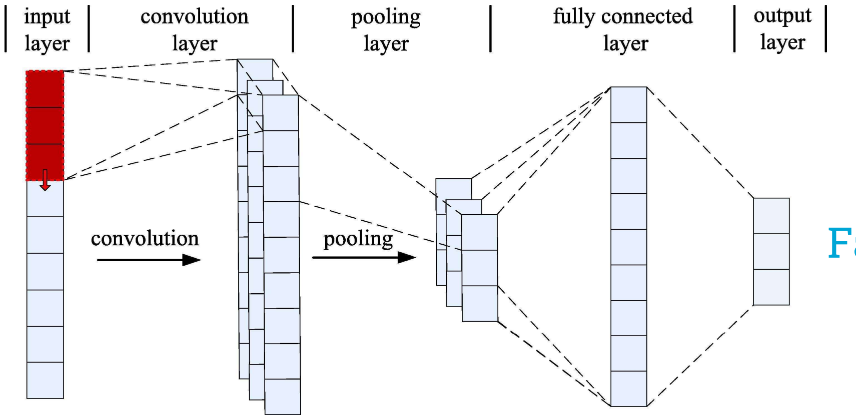
- **Data-driven models**

Data Preparation → Feature Selection → Data Scaling → Model Selection and Training → Evaluation

◆ Support Vector Machine (SVM)
◆ Artificial Neural Network (ANN)
◆ Gradient Boosting Decision Tree (GBDT)
◆ Extreme Gradient Boosting (XGBoost)

◆ Convolutional Neural Network (CNN)

Inputs



Fault Labels

◆ Bayesian Optimization for hyperparameters

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Data-driven FDD: Critical Analysis

- **Data-driven models**

Data Preparation → Feature Selection → Data Scaling → Model Selection and Training → Evaluation

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Overall correctness of the model

$$\text{Precision} = \frac{TP}{TP+FP}$$

Correctness of positive predictions

$$\text{Recall} = \frac{TP}{TP+FN}$$

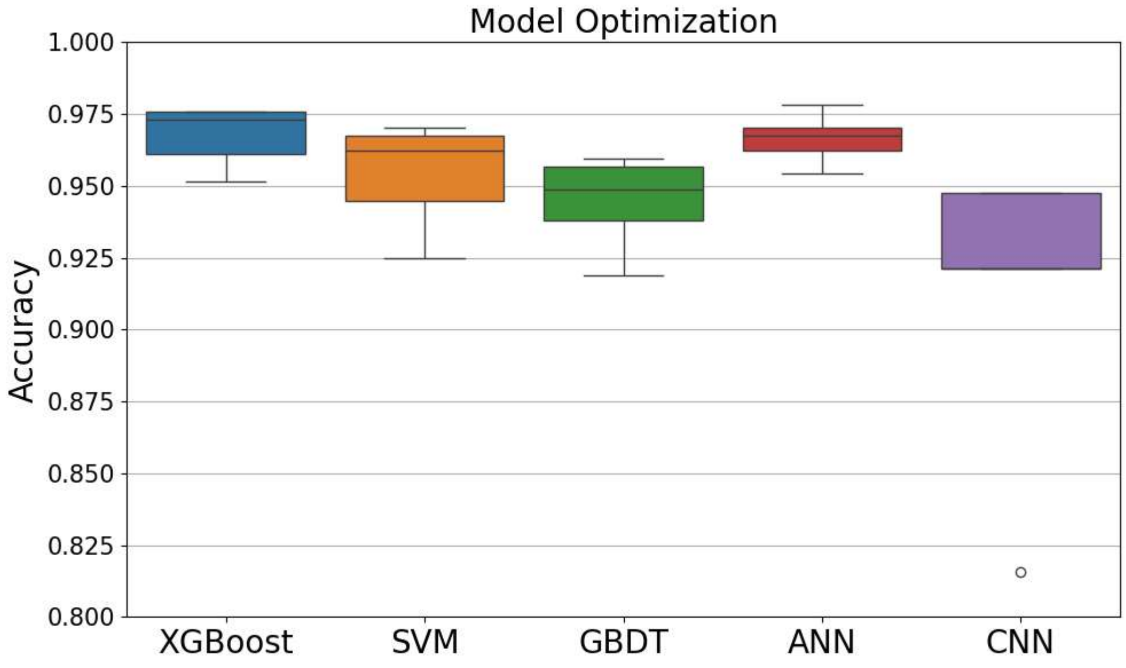
Ability to find all positive instances

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Balance between precision and recall

Data-Driven FDD: Critical Analysis

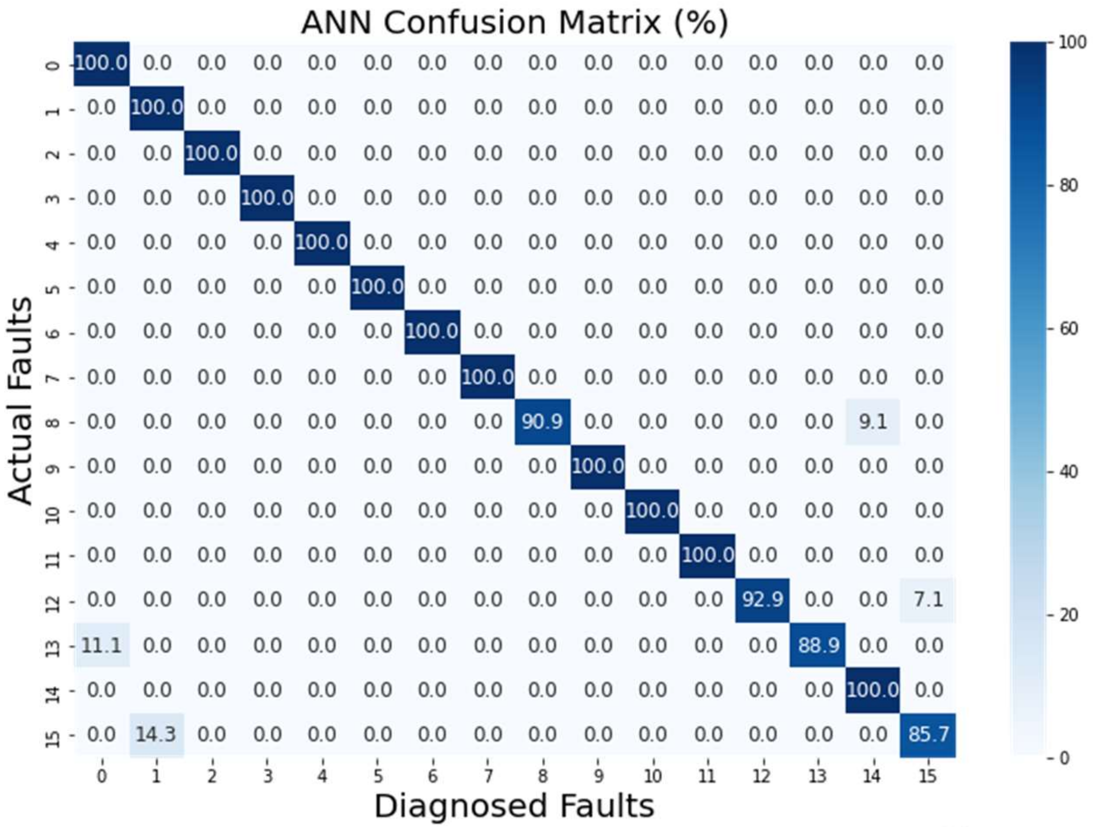
- **Bayesian Optimization for hyperparameters**



Data-Driven FDD: Critical Analysis

- **How accurate data-driven models can be?**

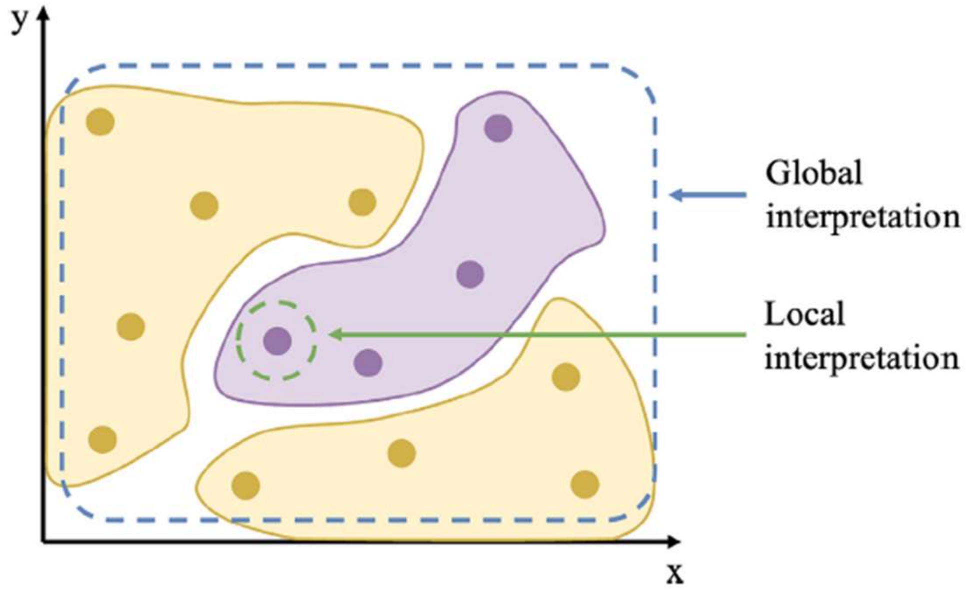
	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	**97.5**	**97.82**	**97.5**	97.51
GBDT	95.63	96.02	95.63	95.54
XGBoost	**97.5**	97.71	**97.5**	97.48
ANN	**97.5**	97.76	**97.5**	**97.54**
CNN	93.75	95.31	93.75	93.82



➢ Quite accurate!

Data-Driven FDD: Critical Analysis

- **Can data-driven models be trustworthy?**

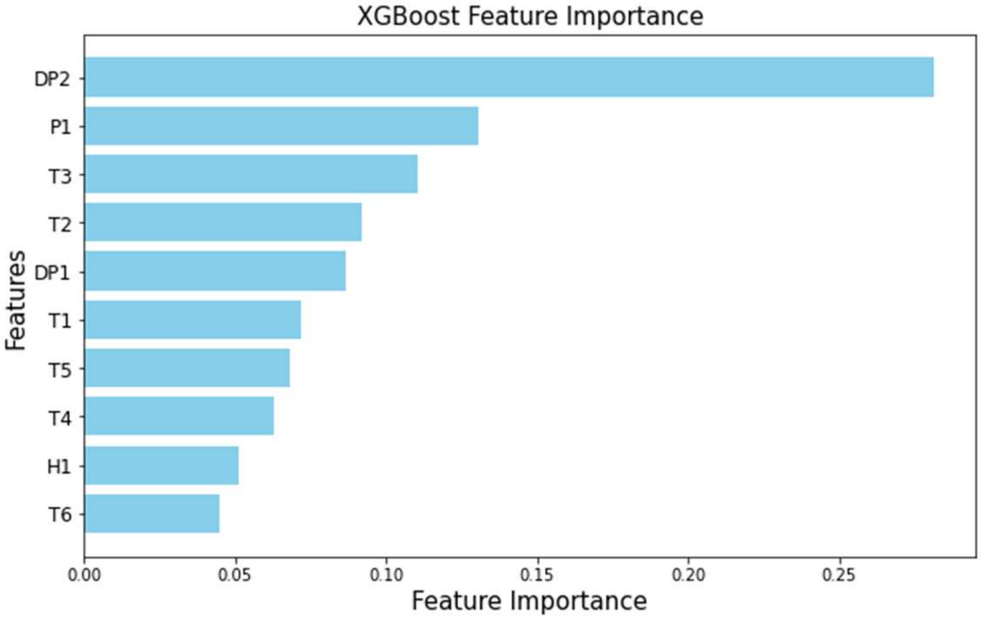


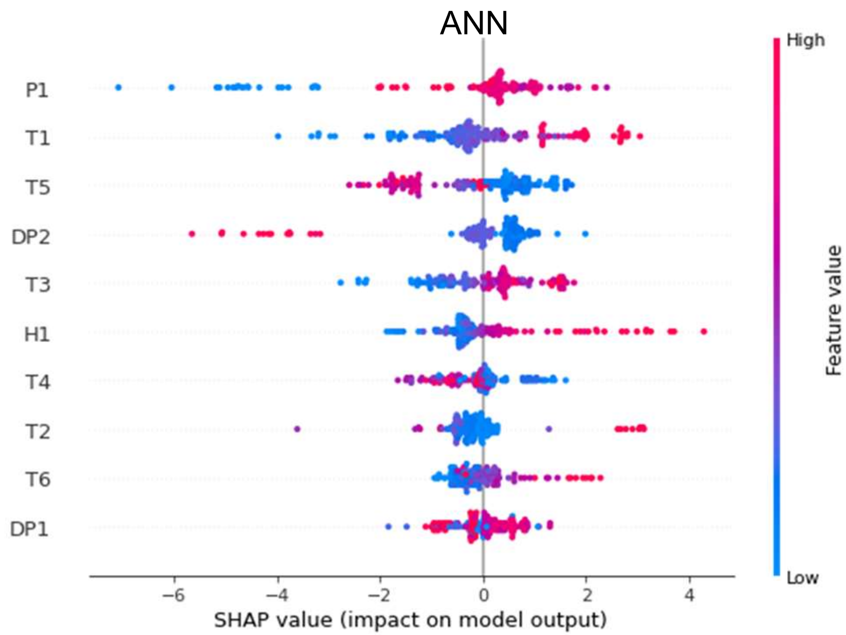
- **Holistic understanding** of the ML model by measuring the global effects of the input features on the diagnosis.
- Transparent understanding of the diagnosis for a **specific sample**.

Chen et al., Adv. in Appl Energy (2019)

Data-Driven FDD: Critical Analysis

- **Can data-driven models be trustworthy?**
  - ➢ Global interpretation:

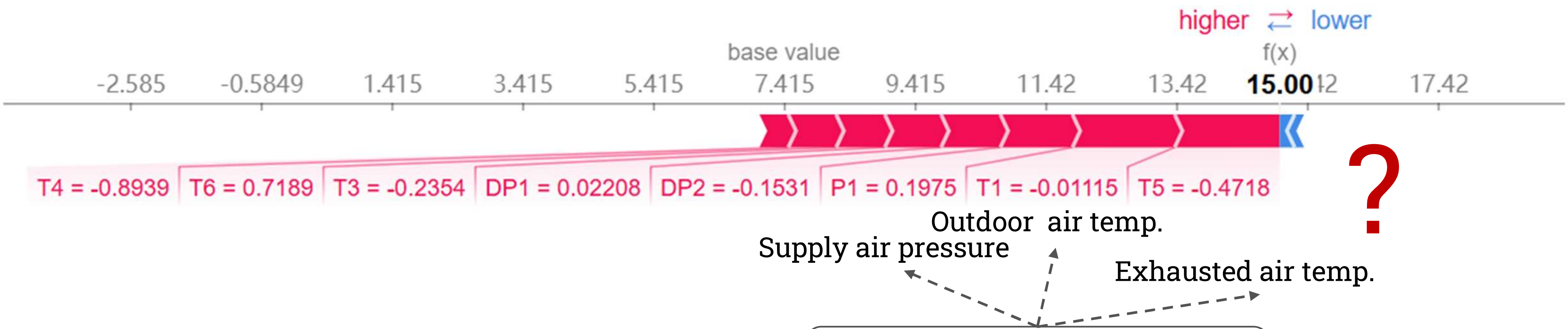




◆ Strange!

Data-Driven FDD: Critical Analysis

- **Can data-driven models be trustworthy?**
  - ➢ Local interpretation



F15: Incorrect supply air temp. sensor reading (17℃)

◆ Doubtful!
Diagnosis (decision-making) seems based irrelevant information, rather than fault pattern!

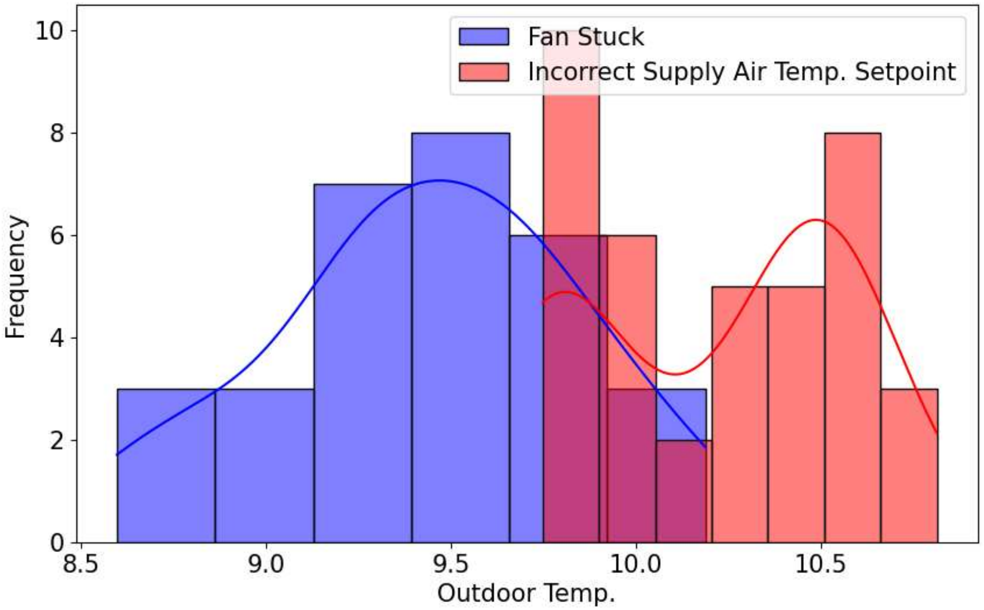
Data-Driven FDD: Critical Analysis

- **Why data-driven models cannot be trustworthy?**

High-quality data:
- Data from sufficient sensors √
- Data without missing values √
- Data with faulty labels √
- Data with balanced labels √
- Data with generalized distributions **?**
- ...

Outdoor temp. distributions provide significant diagnostic evidence. But it is not relevant !

Reason: limited data collection experiments
- "Fan Stuck" was collected from 9 to 11
- "Incorrect Supply Air Temp. Setpoint" was collected from 13 to 17



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Data-Driven FDD: Critical Analysis

- **Can data-driven models be transferable?**

Offline Training

Online Testing (Diagnose)

?

- *Similar AHU*
- *Different equipment (Brand)*
- *Different control strategy*
- *Different installation*

Type	Fault	State	Samples	No.
Component	Fan Stuck	30%	30	F_1
	Heat Recovery Wheel	0%	27	F_3
	Stuck	30%	34	F_4
	Heating Coil Valve Stuck	100%	36	F_8

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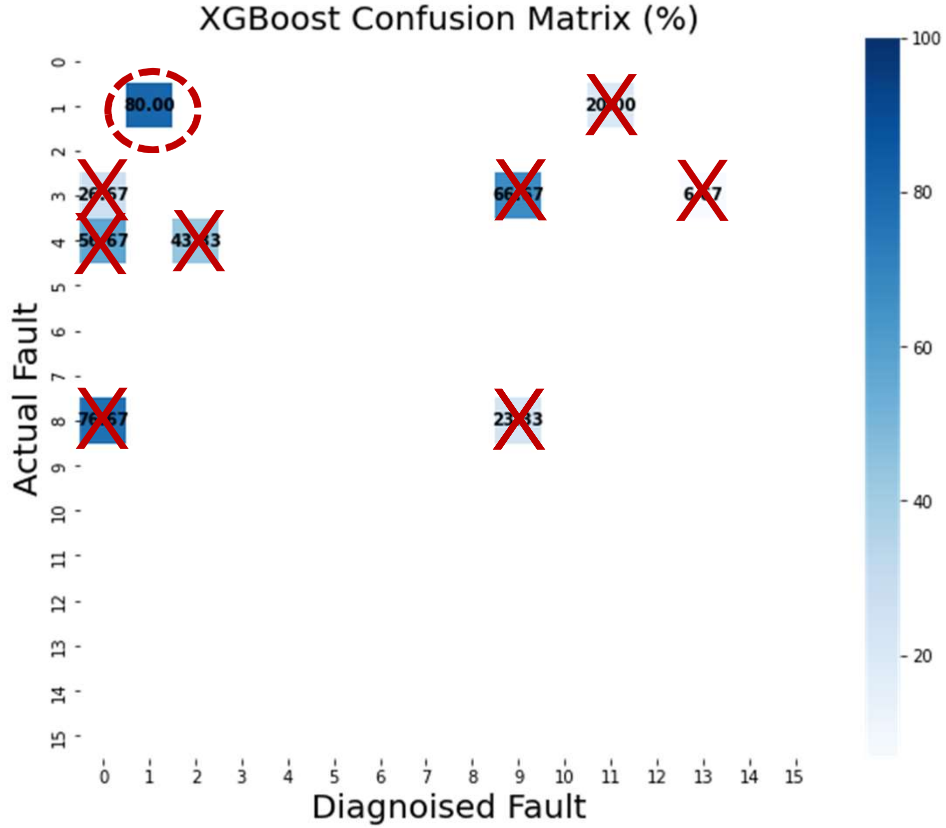
Data-Driven FDD: Critical Analysis

- **Can data-driven models be transferable?**

	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	0	0	0	0
GBDT	4.17	25	4.17	7.14
XGBoost	20	25	20	22.22
ANN	0.83	25	0.83	1.61
CNN	0	0	0	0



➢ NO.
Data-driven models can not be transferred **directly** to other buildings

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Data-Driven FDD: Critical Analysis

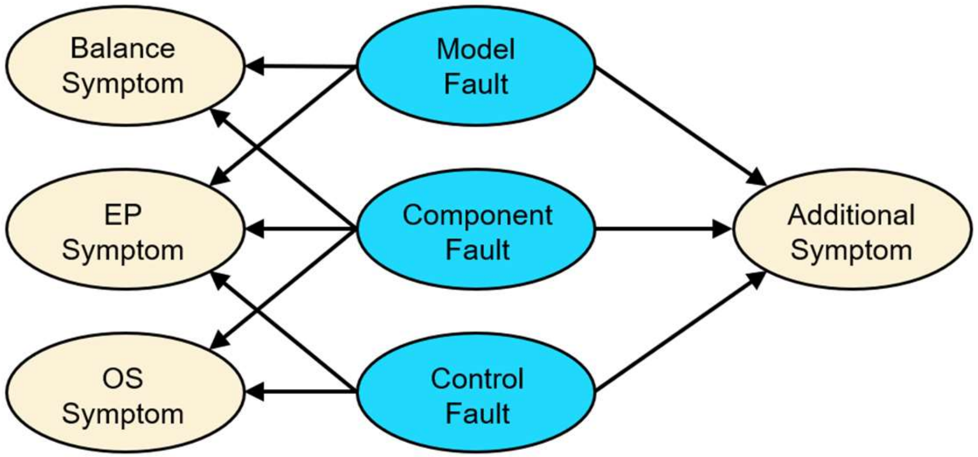
- **Summary: Don't be fooled by accuracy!**
  - **Data :**
    - Collect more?

  - **Data-driven Model** :
    - Unsupervised learning?
    - Transferring learning?
    - Active learning?
    - Federated Learning?
    - Integrated with engineering knowledge?

Diagnostic Bayesian Network (DBN)

*DBN aligns well with HVAC design and implementation practices, which can be a more **generalized applicable FDD solution in industry***

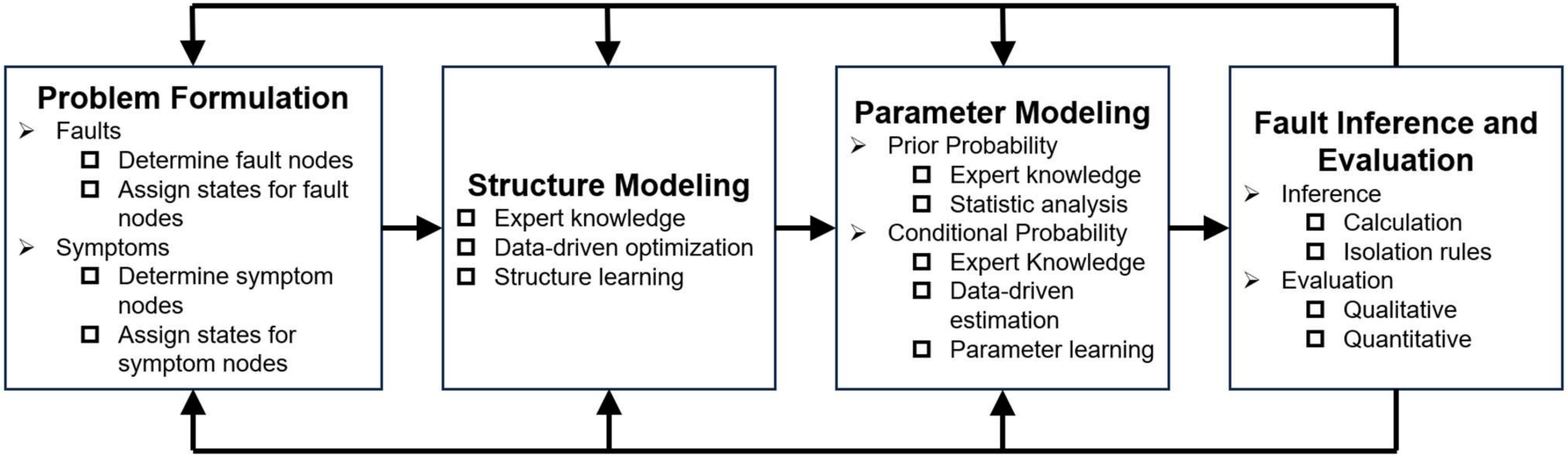
- **Robustness to Uncertainties**
- **Interpretability**
- **Scalability**
- **Flexibility**



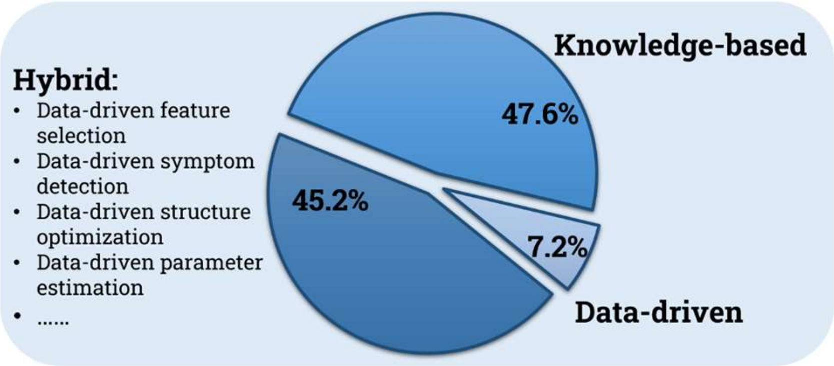
Four symptoms and three faults (4S3F) approach

Diagnostic Bayesian Network (DBN)

- **Generic modeling procedure**



➢ **Flexibility:** DBN modeling can be knowledge-based or data-driven, or hybrid.

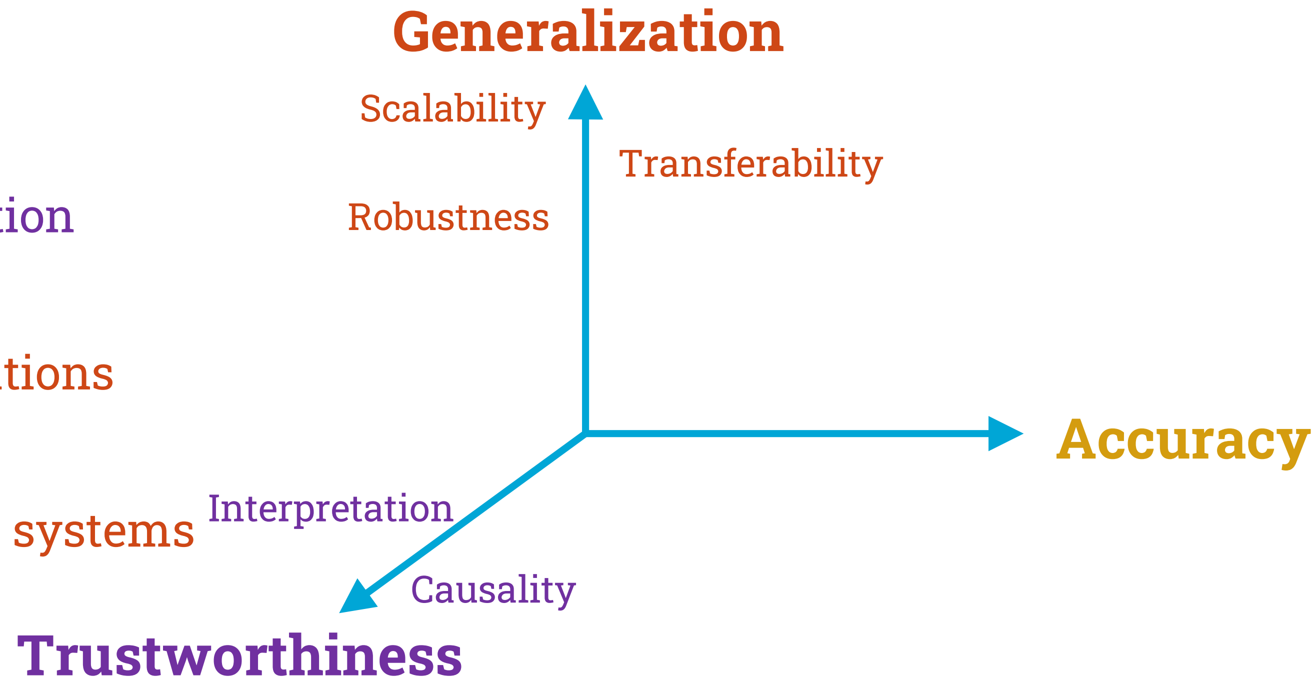


Ongoing research

- DBN for case studies in the context of northern Europe
- DBN with occupant feedback
- Real-time implementation

- Causality-informed symptom detection

- DBN under diverse sensor configurations
- Generalized DBN library
- DBN for multi-scale building energy systems
- Adaptive DBN



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BRAINS 4 BUILDINGS

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  (CRE TUD) Danny Pronk, Serkan Simsir, …

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