ANNEX 81

EBC

Energy in Building and Communities Programme

International Energy Agency

Annex 81 Final Report

Energy in Buildings and Communities Technology Collaboration Programme

June 2025

Technology Collaboration Programme by iea

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Preface

The International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the framework of the Organisation for Economic Co-operation and Development (OECD) to implement an international energy programme. A basic aim of the IEA is to foster international co-operation among the 30 IEA participating countries and to increase energy security through energy research, development and demonstration in the fields of technologies for energy efficiency and renewable energy sources.

The IEA Energy in Buildings and Communities Programme

The IEA co-ordinates international energy research and development (R&D) activities through a comprehensive portfolio of Technology Collaboration Programmes (TCPs). The mission of the IEA Energy in Buildings and Communities (IEA EBC) TCP is to support the acceleration of the transformation of the built environment towards more energy efficient and sustainable buildings and communities, by the development and dissemination of knowledge, technologies and processes and other solutions through international collaborative research and open innovation. (Until 2013, the IEA EBC Programme was known as the IEA Energy Conservation in Buildings and Community Systems Programme, ECBCS.)
The high priority research themes in the EBC Strategic Plan 2019-2024 are based on research drivers, national programmes within the EBC participating countries, the Future Buildings Forum (FBF) Think Tank Workshop held in Singapore in October 2017 and a Strategy Planning Workshop held at the EBC Executive Committee Meeting in November 2017. The research themes represent a collective input of the Executive Committee members and Operating Agents to exploit technological and other opportunities to save energy in the buildings sector, and to remove technical obstacles to market penetration of new energy technologies, systems and processes. Future EBC collaborative research and innovation work should have its focus on these themes.
At the Strategy Planning Workshop in 2017, some 40 research themes were developed. From those 40 themes, 10 themes of special high priority have been extracted, taking into consideration a score that was given to each theme at the workshop. The 10 high priority themes can be separated in two types namely 'Objectives' and 'Means'. These two groups are distinguished for a better understanding of the different themes.

Objectives - The strategic objectives of the EBC TCP are as follows:

- reinforcing the technical and economic basis for refurbishment of existing buildings, including financing, engagement of stakeholders and promotion of co-benefits;
- improvement of planning, construction and management processes to reduce the performance gap between design stage assessments and real-world operation;
- the creation of 'low tech', robust and affordable technologies;
- the further development of energy efficient cooling in hot and humid, or dry climates, avoiding mechanical cooling if possible;
- the creation of holistic solution sets for district level systems taking into account energy grids, overall performance, business models, engagement of stakeholders, and transport energy system implications.

Means - The strategic objectives of the EBC TCP will be achieved by the means listed below:

- the creation of tools for supporting design and construction through to operations and maintenance, including building energy standards and life cycle analysis (LCA);
- benefitting from 'living labs' to provide experience of and overcome barriers to adoption of energy efficiency measures;
- improving smart control of building services technical installations, including occupant and operator interfaces;
- addressing data issues in buildings, including non-intrusive and secure data collection;
- the development of building information modelling (BIM) as a game changer, from design and construction through to operations and maintenance.

The themes in both groups can be the subject for new Annexes, but what distinguishes them is that the 'objectives' themes are final goals or solutions (or part of) for an energy efficient built environment, while the 'means' themes are instruments or enablers to reach such a goal. These themes are explained in more detail in the EBC Strategic Plan 2019-2024.

The Executive Committee

Overall control of the IEA EBC Programme is maintained by an Executive Committee, which not only monitors existing projects, but also identifies new strategic areas in which collaborative efforts may be beneficial. As the Programme is based on a contract with the IEA, the projects are legally established as Annexes to the IEA EBC Implementing Agreement. At the present time, the following projects have been initiated by the IEA EBC Executive Committee, with completed projects identified by (*) and joint projects with the IEA Solar Heating and Cooling Technology Collaboration Programme by (☼):

Annex 1: Load Energy Determination of Buildings (*)
Annex 2: Ekistics and Advanced Community Energy Systems (*)
Annex 3: Energy Conservation in Residential Buildings (*)
Annex 4: Glasgow Commercial Building Monitoring (*)
Annex 5: Air Infiltration and Ventilation Centre
Annex 6: Energy Systems and Design of Communities (*)
Annex 7: Local Government Energy Planning (*)
Annex 8: Inhabitants Behaviour with Regard to Ventilation (*)
Annex 9: Minimum Ventilation Rates (*)
Annex 10: Building HVAC System Simulation (*)
Annex 11: Energy Auditing (*)
Annex 12: Windows and Fenestration (*)
Annex 13: Energy Management in Hospitals (*)
Annex 14: Condensation and Energy (*)
Annex 15: Energy Efficiency in Schools (*)
Annex 16: BEMS 1- User Interfaces and System Integration (*)
Annex 17: BEMS 2- Evaluation and Emulation Techniques (*)
Annex 18: Demand Controlled Ventilation Systems (*)
Annex 19: Low Slope Roof Systems (*)
Annex 20: Air Flow Patterns within Buildings (*)
Annex 21: Thermal Modelling (*)
Annex 22: Energy Efficient Communities (*)
Annex 23: Multi Zone Air Flow Modelling (COMIS) (*)
Annex 24: Heat, Air and Moisture Transfer in Envelopes (*)
Annex 25: Real time HVAC Simulation (*)
Annex 26: Energy Efficient Ventilation of Large Enclosures (*)
Annex 27: Evaluation and Demonstration of Domestic Ventilation Systems (*)
Annex 28: Low Energy Cooling Systems (*)
Annex 29: ☼ Daylight in Buildings (*)
Annex 30: Bringing Simulation to Application (*)
Annex 31: Energy-Related Environmental Impact of Buildings (*)
Annex 32: Integral Building Envelope Performance Assessment (*)
Annex 33: Advanced Local Energy Planning (*)
Annex 34: Computer-Aided Evaluation of HVAC System Performance (*)
Annex 35: Design of Energy Efficient Hybrid Ventilation (HYBVENT) (*)
Annex 36: Retrofitting of Educational Buildings (*)
Annex 37: Low Exergy Systems for Heating and Cooling of Buildings (LowEx) (*)
Annex 38: ☼ Solar Sustainable Housing (*)
Annex 39: High Performance Insulation Systems (*)
Annex 40: Building Commissioning to Improve Energy Performance (*)
Annex 41: Whole Building Heat, Air and Moisture Response (MOIST-ENG) (*)
Annex 42: The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (FC+COGEN-SIM) (*)
Annex 43: ☼ Testing and Validation of Building Energy Simulation Tools (*)
Annex 44: Integrating Environmentally Responsive Elements in Buildings (*)
Annex 45: Energy Efficient Electric Lighting for Buildings (*)
Annex 46: Holistic Assessment Tool-kit on Energy Efficient Retrofit Measures for Government Buildings (EnERGo) (*)
Annex 47: Cost-Effective Commissioning for Existing and Low Energy Buildings (*)
Annex 48: Heat Pumping and Reversible Air Conditioning (*)
Annex 49: Low Exergy Systems for High Performance Buildings and Communities (*)
Annex 50: Prefabricated Systems for Low Energy Renovation of Residential Buildings (*)
Annex 51: Energy Efficient Communities (*)
Annex 52: ☼ Towards Net Zero Energy Solar Buildings (*)
Annex 53: Total Energy Use in Buildings: Analysis and Evaluation Methods (*)
Annex 54: Integration of Micro-Generation and Related Energy Technologies in Buildings (*)
Annex 55: Reliability of Energy Efficient Building Retrofitting - Probability Assessment of Performance and Cost (RAP-RETRO) (*)
Annex 56: Cost Effective Energy and CO2 Emissions Optimization in Building Renovation (*)
Annex 57: Evaluation of Embodied Energy and CO2 Equivalent Emissions for Building Construction (*)

Annex 58: Reliable Building Energy Performance Characterisation Based on Full Scale Dynamic Measurements (*)
Annex 59: High Temperature Cooling and Low Temperature Heating in Buildings (*)
Annex 60: New Generation Computational Tools for Building and Community Energy Systems (*)
Annex 61: Business and Technical Concepts for Deep Energy Retrofit of Public Buildings (*)
Annex 62: Ventilative Cooling (*)
Annex 63: Implementation of Energy Strategies in Communities (*)
Annex 64: LowEx Communities - Optimised Performance of Energy Supply Systems with Exergy Principles (*)
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Annex 68: Indoor Air Quality Design and Control in Low Energy Residential Buildings (*)
Annex 69: Strategy and Practice of Adaptive Thermal Comfort in Low Energy Buildings (*)
Annex 70: Energy Epidemiology: Analysis of Real Building Energy Use at Scale (*)
Annex 71: Building Energy Performance Assessment Based on In-situ Measurements (*)
Annex 72: Assessing Life Cycle Related Environmental Impacts Caused by Buildings (*)
Annex 73: Towards Net Zero Energy Resilient Public Communities (*)
Annex 74: Competition and Living Lab Platform (*)
Annex 75: Cost-effective Building Renovation at District Level Combining Energy Efficiency and Renewables (*)
Annex 76: ☼ Deep Renovation of Historic Buildings Towards Lowest Possible Energy Demand and CO_2 Emissions (*)
Annex 77: ☼ Integrated Solutions for Daylight and Electric Lighting (*)
Annex 78: Supplementing Ventilation with Gas-phase Air Cleaning, Implementation and Energy Implications
Annex 79: Occupant-Centric Building Design and Operation (*)
Annex 80: Resilient Cooling of Buildings (*)
Annex 81: Data-Driven Smart Buildings
Annex 82: Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems
Annex 83: Positive Energy Districts
Annex 84: Demand Management of Buildings in Thermal Networks
Annex 85: Indirect Evaporative Cooling
Annex 86: Energy Efficient Indoor Air Quality Management in Residential Buildings
Annex 87: Energy and Indoor Environmental Quality Performance of Personalised Environmental Control Systems
Annex 88: Evaluation and Demonstration of Actual Energy Efficiency of Heat Pump Systems in Buildings
Annex 89: Ways to Implement Net-zero Whole Life Carbon Buildings
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Annex 91: Open BIM for Energy Efficient Buildings
Annex 92: Smart Materials for Energy-Efficient Heating, Cooling and IAQ Control in Residential Buildings
Annex 93: Energy Resilience of the Buildings in Remote Cold Regions
Annex 94: Validation and Verification of In-situ Building Energy Performance Measurement Techniques
Annex 95: Human-centric Building Design and Operation for a Changing Climate
Annex 96: Grid Integrated Control of Buildings

Working Group - Energy Efficiency in Educational Buildings (*)
Working Group - Indicators of Energy Efficiency in Cold Climate Buildings (*)
Working Group - Annex 36 Extension: The Energy Concept Adviser (*)
Working Group - HVAC Energy Calculation Methodologies for Non-residential Buildings (*)
Working Group - Cities and Communities
Working Group - Building Energy Codes

Summary

IEA-EBC Annex 81 investigated emerging 'Artificial Intelligence' software tools for optimising energy consumption, in digitally enabled 'Smart Buildings'. These software tools include automated Fault Detection and Diagnosis (FDD), Model Predictive Control (MPC) and Buildings to Grid (B2G) applications. This work was initiated by the Mission Innovation 'Affordable Heating and Cooling Innovation Challenge'.

These technologies can reduce energy waste by up to 40%. They also provide 'dispatchability' (sometimes called 'flexibility'). Dispatchability is a critical resource for backing up variable renewable energy generation sources, as part of the global clean energy transition.

The US Department of Energy (2021) estimates that 'Grid-Interactive Efficient Buildings' (GEBs) have the potential to reduce total U.S. electricity supply costs by 2 to 6% (saving the US power system $100-200 billion by 2040) and helping to reduce CO_2 emissions by around 6% (saving around 80 MT/year of CO2 emissions).

In addition to energy bill savings for building owners, digitalisation is a critical enabler (at energy system-level) for matching energy supply and demand. It can also underpin the implementation of government policies aimed at improving the efficiency of energy markets. The IEA identified '*Leveraging digital innovation to enhance system-wide efficiency*' as one of its ten strategic principles for achieving the COP28 goals.

Recommendations For Policy Makers

Consistent with the IEA Net Zero by 2050 Scenario, policy makers should set the following 'digital-ready' targets, in order to reduce consumer energy bills by 20%.

- All new buildings to be flexible resources by 2030; and
- 85% of all existing buildings to be retrofitted by 2050 with efficient and grid-interactive appliances.

Numerous roadmaps agree that achieving these targets will require government to play a coordinating role, to overcome industry barriers and support adoption of digitalisation in buildings.

Consultation with industry identified key actions that government can take. These actions are illustrated in the Annex 81 'Policy Package for Energy Optimisation in Buildings through Digitalisation' (see Figure below). They are summarised as follows.

1. Interoperability and data access barriers:

Government should publish guides with clear terminology to describe best practice digitalisation concepts (Action 1.2). Standardisation begins with the use of common language.

- These concepts should be enshrined as standards and/or other requirements or specifications.
  - Industry adoption can then be driven by including these requirements in construction codes (Action 2.1), certification/rating schemes (Action 2.2), incentive schemes (Action 2.3) and/or mandatory equipment specifications (Action 8.2).
  - Relevant rating schemes, incentive schemes and/or markets will require certain data inputs. Regulatory support should be given, to ensure that these data inputs are available as standard (Action 6.1, Action 6.2), and access is not subject to commercial and/or privacy constraints.
  - Government operated data platforms (linked to relevant government schemes) can play a key role in supporting efficient and scalable collection of standard data from industry (Action 6.3, Action 8.5).
- Government can play a key role in driving critical mass industry adoption of standards (and relevant voluntary schemes) by, for example, adopting digital ready clauses for its own buildings (e.g. through 'green-leases' (Action 3.3)).

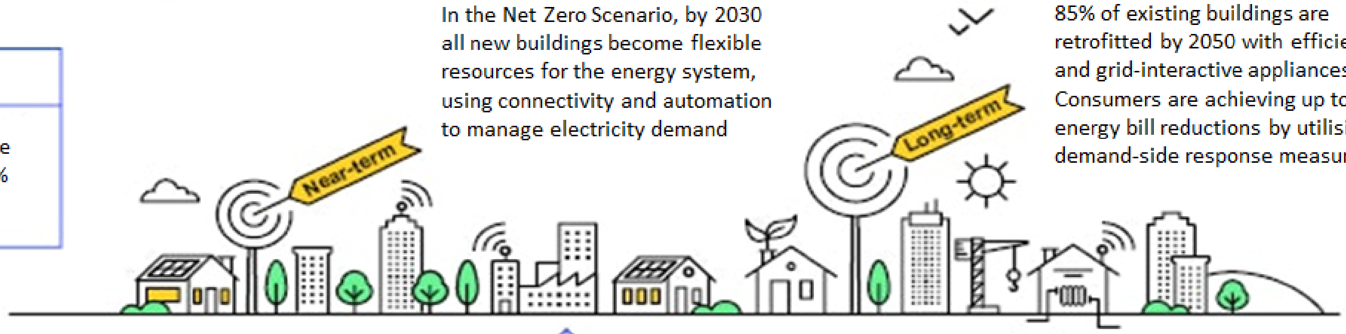
Policy Package – Energy Optimisation in Buildings through Digitalisation

Immediate opportunities

Digitalisation can help reduce energy wastage by up to 40% in commercial buildings

In the Net Zero Scenario, by 2030 all new buildings become flexible resources for the energy system, using connectivity and automation to manage electricity demand

85% of existing buildings are retrofitted by 2050 with efficient and grid-interactive appliances. Consumers are achieving up to 20% energy bill reductions by utilising demand-side response measures



REGULATION

Theme 2: Establish 'digital ready' certification

2.1 Use construction codes to require new buildings to achieve minimum 'digital ready' levels

Theme 6: Reduce data-sharing risks

6.1 Clarify consumer data rights regarding energy data
6.2 Regulate energy data to be collected, use of standard data collection formats and how data can be shared (including provision of price signals)

Theme 8: Integrate buildings into the electricity system

8.1 Reform electricity market rules to encourage participation of DER from Grid Interactive Buildings.
8.2 Require demand-response readiness in MEPS for major appliances
8.3 Place obligations on retailers to support customers to deliver demand flexibility services

INFORMATION

Theme 1: Provide information

1.1 Collate and disseminate knowledge from pilot buildings.
1.2 Prepare guides and terminology for digital infrastructure and data management practices

Theme 2: Establish 'digital ready' certification

2.2 Use 'digital ready' standards and criteria to establish a certification system for recognizing achievement of 'digital ready' status

Theme 3: Government leading by example

3.1 Maintain a centralised expert team to support agencies

Theme 4: Support researchers and innovators

4.1 Engage the research sector in testing, analysis, knowledge sharing and developing tools and standards

Theme 7: Build workforce skills and capacity

7.1 Support digital training across the property sector
7.2 Create incentive strategies for attracting IT talent into the property sector

INCENTIVES

Theme 2: Establish 'digital ready' certification

2.3 Reward achievement of 'digital ready' in a relevant rating scheme and/or as eligibility criteria for an incentive mechanism

Theme 3: Government leading by example

3.2 Invest in digitalisation technology in government buildings
3.3 Adopt 'digital ready' green lease clauses

Theme 4: Support researchers and innovators

4.2 Provide funding and test buildings to help innovators develop and commercialisation new smart products

Theme 5: Incentivise EMIS technology

5.1 Provide co-investment grants or tax incentives
5.2 Recognise EMIS technology in performance-based energy savings schemes
5.3 Authorise M&V methodologies and automated tools

Theme 6: Reduce data-sharing risks

6.3 Provide data stewardship/ data-hub services

Theme 8: Integrate buildings into the electricity system

8.4 Catalyse the market by acquiring a target amount of DER from Grid Interactive Buildings
8.5 Establish a market operations platform to support DER from Grid Interactive Buildings

2. Economic and first cost sensitivity barriers:

Government should support competitive markets that can drive efficient energy management outcomes through digitalisation. Artificial barriers that prevent demand management resources from participating in energy markets should be removed (Action 8.1).

- Certificate Schemes (Action 5.2, Action 8.3) are a proven policy mechanism with high benefit to cost ratios. Certificate schemes should be designed to achieve a target amount of digitally-enabled DER in Grid Interactive Buildings, as the intended policy outcome (Action 8.4)
    - Energy management incentive schemes will often need measurement and verification (M&V) to quantify and reward actions, in a performance-based way. Government-approved, digitally-automated M&V tools should be provided to industry - to streamline participation in markets and schemes (Action 5.3).
- While industry felt that digitalisation products and services can already compete without subsidies, industry adoption could be accelerated (in the short term) through direct incentives (Action 5.1, Action 2.3) and through mandated adoption in government buildings (Action 3.3).

3. Workforce skills and capacity barriers:

Government should develop an education and training agenda for improving digital skills in the property industry (Action 7.1, Action 7.2).

- Government can help improve focus on these skills by establishing digitalisation centres of excellence in both academia (Action 4.1) and government facilities management (Action 3.1).

4. Information and implementation complexity barriers:

Government should fund case-studies and pilots (Action 4.2, Action 5.1).

- Funding for case studies should be contingent on thorough knowledge-sharing using independent research bodies (Action 4.1).
    - Knowledge should be consolidated and shared through established professional channels, with media tailored to the needs of decision makers (Action 1.1).
    - Where possible, knowledge should be synthesised into relevant guides and standards that de-risk implementation (Action 1.2).
- Government can play a key role in creating information resources by investing in digitalisation technology across its own building portfolio (Action 3.2) and sharing the resulting knowledge.
    - Government should recruit a specialist centralised team with digitalisation expertise (Action 3.1), to support (de-risk) implementation in its own buildings, and to ensure that there is appropriate expert knowledge sharing.

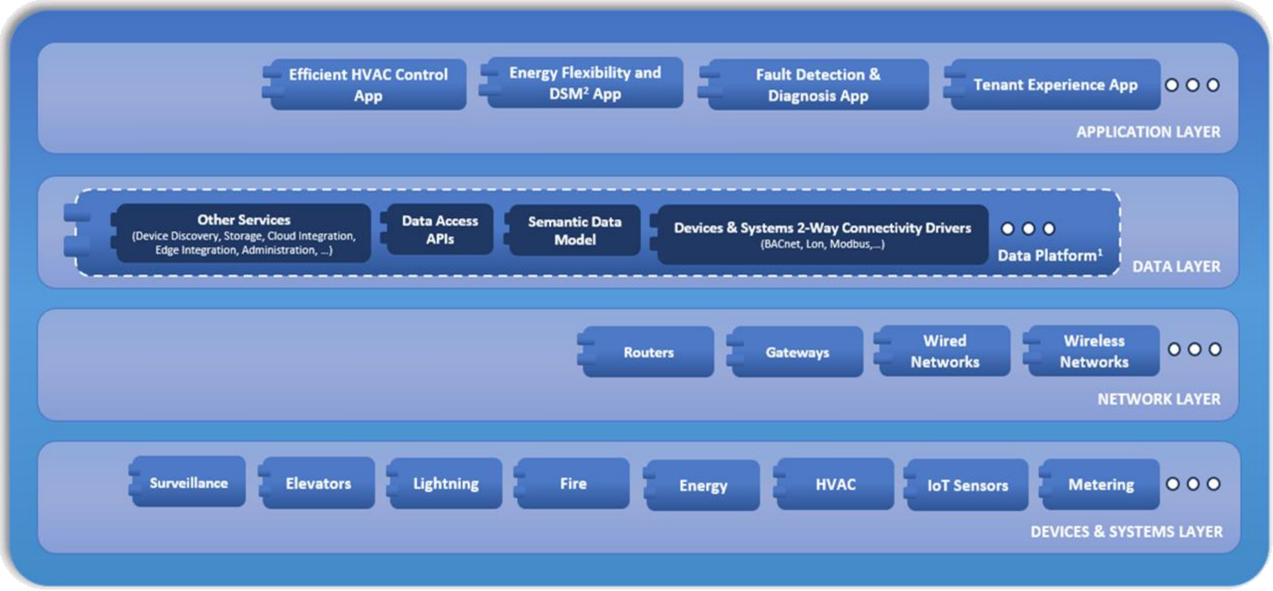
Examples of government initiatives that have enshrined various of these recommendations are provided in Section 6.

Background and context

Data quality and data management practices are critical

Access to data is core to the success of data-driven AI applications in smart buildings. This requires appropriate digital infrastructure in a building, and attention to data governance. Stakeholder interviews identified data quality and data management as one of the most critical industry issues.

Annex 81 participants recommend digital infrastructure (the software/hardware stack required for deploying AI software services in non-residential buildings) that includes the following four 'layers': (i) Device & Systems Layer, (ii) Network Layer, (iii) Data Layer and (iv) Applications Layer.



The purpose of this software/hardware stack is to create a highly flexible digital infrastructure, that gives the building owner control over their digital resources ('data sovereignty') and gives better access to 3rd party software services (choice).

Core to the success of this digital infrastructure is interoperability. Interoperability issues relate to both (i) device-level communications (i.e. avoiding proprietary communication protocols) and (ii) the extent of informational/semantic context that is attached to the sources of data (i.e. ensuring sufficient metadata is available to give meaning to the data sources).

At a philosophical level, building owners should aspire to apply the FAIR data principles. That is, data is most useful when it is Findable, Accessible, Interoperable and Re-useable (FAIR). Metadata – "data about data" – is used to organize the storage of collected data. It is also used by relevant software applications to automatically identify and retrieve data for processing. Capturing metadata is a key part of achieving the FAIR data principles. This can be achieved by using a metadata schema.

Data governance can restrict the ability to share data. If personal data is involved, there must be a legal basis for sharing data and appropriate controls put in place, to ensure that personal data is secure.

The data-layer – which enshrines relevant interoperability and data governance considerations – is typically implemented as a cloud-based data platform. Acquisition of a data platform is a significant strategic decision for a building owner.

The task of implementing digitalisation services, in a given building, can generally be divided into two steps (1) establishing digital infrastructure and associated data management services (the data-layer) and then (2) deploying data-driven software applications (the applications layer). Separating out the delivery of digital infrastructure (step 1), from the delivery of desirable data-analytics applications (step 2), would be an important step forward for the industry.

Annex 81 participants propose that a building that has installed relevant digital infrastructure (i.e. completed step 1) should be termed 'digital-ready'. Incentives, or other recognition, should be given to buildings that achieve this 'digital-ready' objective.

Datasets and performance benchmarking can support innovation

With access to a data platform, a building owner must decide what data to collect. It is generally acknowledged that there is no shortage of data that could be collected. But it can be surprisingly hard to find the data that is needed. For example, in five relatively well instrumented case study buildings, Annex 81 participants found that less than 25% of relevant literature KPIs could actually be computed from available data.

A survey of 65 industry stakeholders found that – when choosing from all the available KPIs – KPIs that relate to occupant needs are typically prioritized, followed by KPIs relating to a building's energy efficiency and operation. Understandably, least concern was given to KPIs relating to electricity grid requirements. Industry stakeholders expressed a desire for government policy to identify and request that some key datasets be collected (particularly data needed for coordinating DER in energy systems).

Datasets, with well documented ground truth data, are also required for ongoing development of software services such as Fault Detection and Diagnosis (FDD), Model Predictive Control (MPC) and Building to Grid (B2G) applications. To address this gap, Annex 81 participants created

- a database of seven FDD datasets from 7 different HVAC systems, with 257 fault cases (at different severity levels), and 8 billion data points,
- a data base of six high quality MPC datasets, from real-world buildings.
- a database of 16 B2G datasets, sourced from literature.

An innovative test environment (the Building Optimisation Testing (BOPTEST) framework) was used to conduct five benchmarking studies relating to relevant data-driven control algorithms. All studies found that Model Predictive Control and Reinforcement Learning controllers substantially out-performed the test building's conventional rule-based control strategies. They provided better thermal comfort for occupants and reduced energy costs by around 20%. The best MPC solutions typically outperformed the best RL solutions.

Benchmarking tools enabled Annex 81 participants to run two data-driven artificial intelligence (AI) competitions: (1) The ADRENALIN Load Disaggregation Challenge, and (2) The BOPTEST Smart Building HVAC Control Challenge. Such competitions are a powerful tool for cost-effectively harnessing the collective intelligence of global participants, to develop innovative machine learning solutions.

Industry can benefit from sharing lessons learnt from case studies

A focus of Annex 81 research was to collect case studies of data-driven smart buildings. The aim of this work was to (i) gather evidence from real-world implementations, (ii) capture stakeholder perspectives and context, (iii) identify and summarise business models, (iv) highlight relevant applications and use-cases, and (v) document specific technologies and technology stacks.

Eighteen case studies were collected. They are available through an online repository. They include a diverse range of building types, applications, and locations across thirteen countries. Across the case studies, challenges revolved around four core themes: i) data quality and management, ii) technology specification and implementation, iii) stakeholder engagement, and iv) governance, compliance, and legal oversight.

An expanded summary of overall Annex findings, and relevant resources produced by the Annex, is provided in Section 7 of this report. More detailed information on data quality and data management practices is provided in Section 2. Stakeholder access and aspirations for data (with particular focus on performance reporting) is discussed in Section 3. The state of the art of key data-driven energy productivity software applications is provided in Section 4. The learnings associated with implementing software-based energy productivity solutions, in case-study buildings, are detailed in Section 5. Finally, Section 6 describes Annex efforts to understand stakeholder barriers and the key actions required to accelerate industry growth.

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Figures

Tables

Abbreviations

Abbreviations	Meaning
AHU	Air Handling Unit
AI	Artificial Intelligence
ANSI	American National Standards Institute
API	Application Programming Interface
App	Software Application
ASHRAE	American Society of Heating Refrigeration and Airconditioning Engineers
BACnet	Building Automation and Control Networks
B2G	Buildings to Grid
BMS	Building Management System
BOPTEST	Building Optimization Testing Framework
BOT	Building Topology Ontology
BSN	Building Services Network
CDR	Correct Diagnosis Rate
CMMS	Computerised Maintenance Management Systems
CSV	Comma Separated Values
CVRMSE	Coefficient of the Variation of the Root Mean Square Error
DBO	Digital Buildings Ontology
DERMS	Distributed Energy Management System
DER	Distributed Energy Resources
DNN	Deep Neural Networks
DR	Demand Response
EMIS	Energy Management Information System
EMS	Energy Management System
ESG	Environmental, Social, and Governance
FAIR	Findable Accessible Interoperable Reuseable
FCU	Fan Coil Unit
FDD	Fault Detection and Diagnosis
FF	Flexibility Factor
FNR	False Negative Rate
FTPS	File Transfer Protocol Secure
GDPR	General Data Protection Regulation
GEB	Grid Integrated Efficient Building
HVAC	Heating, Ventilation, and Air Conditioning
ICN	Integrated Communication Network
IEA	International Energy Agency
IEA-EBC	International Energy Agency Energy in Buildings and Communities
IEQ	Indoor Environment Quality

I/O	Input/Output
IoT	Internet of Things
IP	Internet Protocol
IT	Information Technology
KPI	Key Performance Indicator
LAN	Local Area Network
LF	Load Factor
LSTM	Long Short Term Memory
M&V	Measurement and Verification
MAPE	Mean Absolute Percentage Error
MEPS	Minimum Energy Performance Standards
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
MPC	Model Predictive Control
NABERS	National Australian Built Environment Rating System
PaaS	Platform as a Service
PLC	Programmable Logic Controller
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
RC	Resistance Capacitance
RDF	Resource Description Framework
REC	Real Estate Core
RL	Reinforcement Learning
SaaS	Software as a Service
SAC	Soft Actor Critic
SAREF	Smart Applications REFerence
SDE	Stochastic Differential Equation
SDK	Software Development Kit
SHACL	Shapes Constraint Language
SRI	Smart Readiness Indicator
SSN/SOSA	Semantic Sensor Network/ Sensor, Observation, Sample, and Actuator
TL	Transfer Learning
TPR	True Positive Rate
VAV	Variable Air Volume
VRF	Variable Refrigerant Flow
W3C OWL	World Wide Web Consortium Web Ontology Language

1. Introduction

The International Energy Agency (IEA) Annex 81 “Data-Driven Smart Buildings” is an international collaboration project of the Energy in Buildings and Communities (EBC) Technology Collaboration Programme. Annex 81 is a collaboration across 18 countries and over 50 expert organisations. These organisations include both industry and research participants.

Annex 81 aims to achieve greater understanding and growth in the use of digitalisation, as an enabling tool for improving energy performance in non-residential buildings. A particular focus of Annex 81 is on using near real time data, from energy consuming equipment, to drive advanced analytics that optimise equipment operations. In this way, Annex 81’s focus is on the operational phase of a building’s life-cycle.

Annex 81’s work was initiated and supported by Mission Innovation’s ‘Affordable Heating and Cooling’ Innovation Challenge. The MI challenge identified AI solutions for *predictive maintenance and control optimization* as a critical area for clean-tech innovation.

This report summarises the research and findings of the 4-year collaboration project. It aims to explain what makes a building ‘smart’, and how artificial intelligence (AI) techniques can be developed and deployed to optimise energy use in a building.

1.1 What is a Data-Driven Smart Building?

AlphaBeta (2018) generalised digitalisation as being an automated process from data to decisions. This process includes steps of (i) data capture, (ii) data management (iii) data analysis and (iv) decision and action. This process, along with a sample of the relevant digital technologies involved in each of these steps, is illustrated in Figure 1.1.

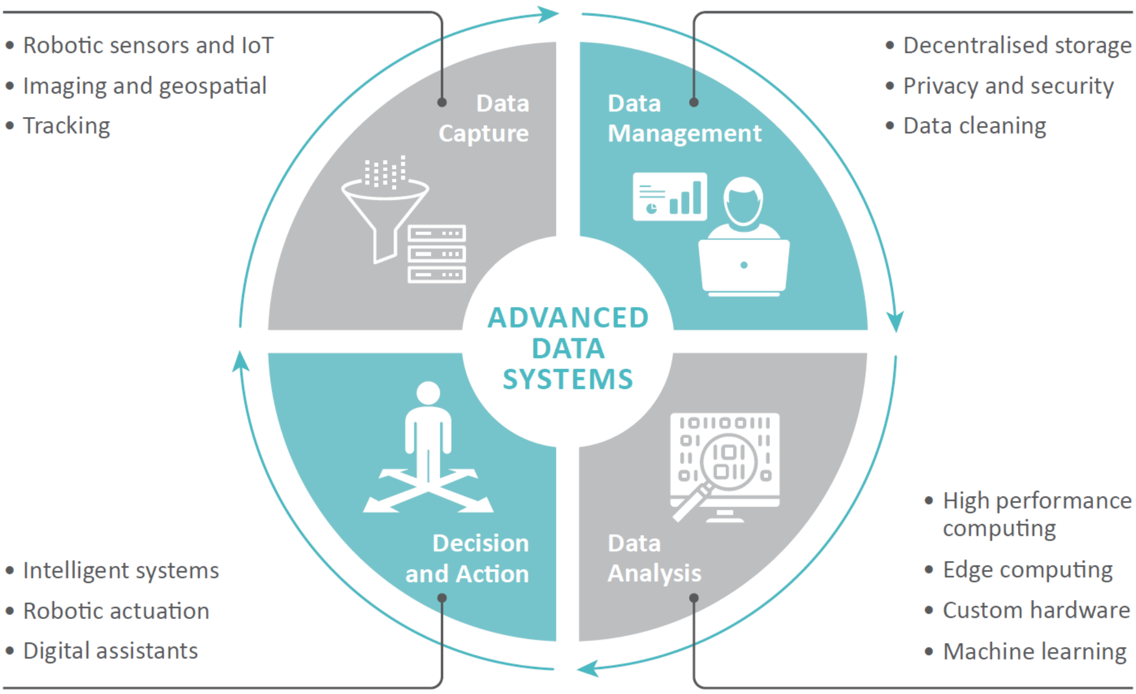

Figure 1.1: Data Innovation Relies on Specialised Systems for Data Capture, Management, Analysis and Action (Source: AlphaBeta, 2018).

From a use-case perspective, digitalisation can be an ***engineering tool***: for automating equipment operations to reduce energy consumption, and to match energy demand with the availability of variable renewable energy resources.

Digitalisation can also be an ***administrative enabler***: for operationalising Government policies that either (i) support building owners with incentives (e.g. rating schemes) or (ii) impose relevant regulatory requirements. Digitalisation is particularly suitable for streamlining measurement and verification (M&V) processes that underpin markets and performance-based assessment (a requirement of many schemes).

In almost all use-cases, digitalisation plays a key role as an ***information sharing tool***: distributing information to where it is needed. Information/data sharing can involve either one-way or two-way communication. Information/data sharing can be machine to human (providing decision support for manual interventions), or machine to machine (automating dynamic processes).

This data-driven approach is potentially highly scalable, for industry, because:

- It reduces the need for skilled practitioners to devote time to understanding the features and operation of a building and it avoids manual coding of rules-based computational models,
- It can utilise powerful analytical tools (e.g. machine learning algorithms) that have already been adopted and proven in other industries), and
- It utilises IT infrastructure and methods that support automated processing of data and digital communication between machines/devices, and with user friendly interfaces for humans.

One exciting opportunity arising from digitalisation, is the ability to apply AI to data emanating from connected buildings. This can be used to improve the operation of buildings. With sufficient 'intelligence', the claim is that physical assets in a building can autonomously select an informed course of action for achieving higher-level objectives (e.g. optimising energy use, IEQ, occupant experience etc).

Incorporating these concepts, Annex 81 participants collectively agreed on the following definition for a 'Data-Driven Smart Building':

> *A Data-Driven Smart Building is a building that uses digitalisation technologies to dynamically optimise its operation, where optimisation objectives typically relate to site energy use, IEQ, and occupant experience.*
>
> *Ideally, it is sufficiently connected and integrated with markets and processes, that it can adaptively respond to externalities and changing conditions (e.g. weather, electricity prices, energy supply constraints, equipment maintenance, etc). Ideally, it has sufficient memory of past events, and ability to anticipate future impacts, that it can select an informed course of action for achieving higher-level objectives – reminiscent of human intelligence.*
>
> *To achieve this vision, a Data-Driven Smart Building utilises both live and historical data from relevant sensors, IoT equipment, mobile devices, and other sources, to provide situational awareness for informed decision-making. Achieving optimisation objectives will often benefit from advanced supervisory-level automation, driven by computational analysis (e.g. Machine Learning, AI, etc) applied to available data.*

Locatee and Memoori (2017) identify seven attributes of Smart Buildings. Each of these attributes provides the basis for a set of use-cases (applications), which can deliver tangible benefits in the form of (i) higher operational efficiency and resource utilisation, (ii) improved user experience and indoor environment for building occupants, (iii) information distribution between stakeholders and (iv) risk mitigation.

All of these applications will have different data needs, as inputs for automated decisions and actions. Of most interest to the International Energy Agency are the various energy productivity applications[1]. These applications are illustrated in Figure 1.2. It should be noted, however, that non-energy related co-benefits (from digitalisation) can be an important motivator for investment decisions, and should not be ignored.

[1] Energy productivity is a term used to include all the various forms of useful energy services – including energy efficiency, load shaping and flexible demand services

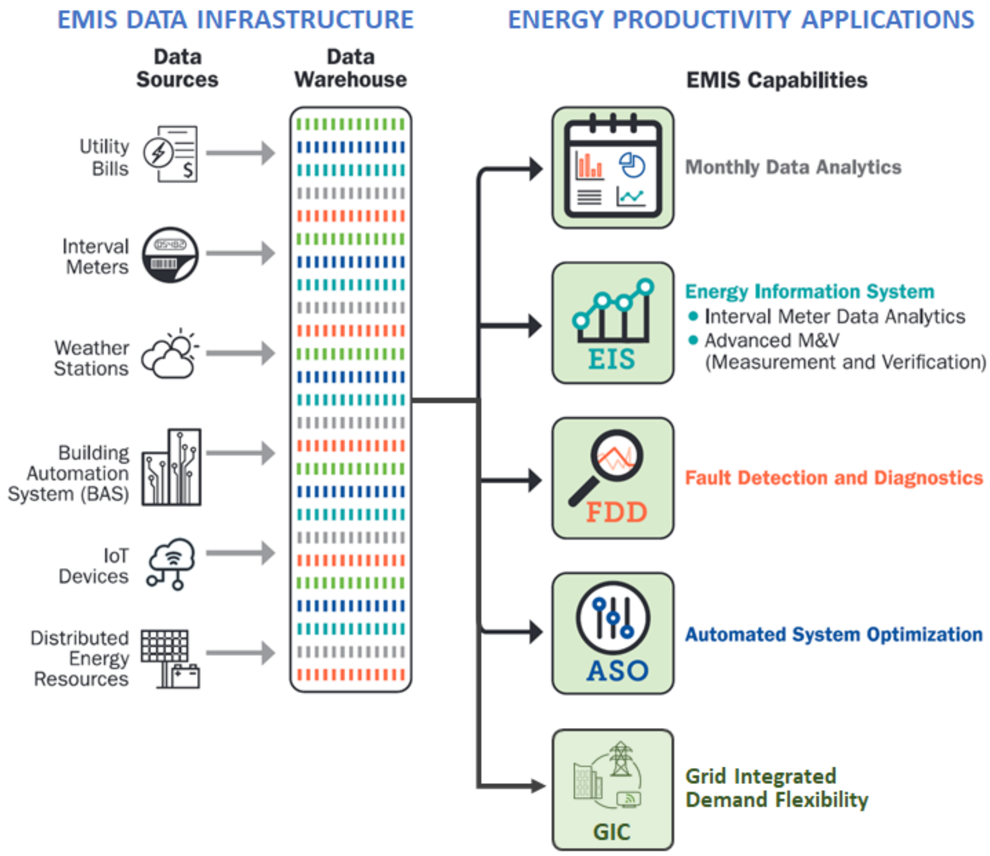

Figure 1.2: Typical energy productivity applications that can be hosted on a data platform (adapted from Kramer et al, 2020)

Figure 1.2 usefully distinguishes between the data collection/management infrastructure and the software applications that perform relevant analytics based energy-productivity services. Kramer *et al.* (2020) call this combination of tools and data flows an Energy Management Information System (EMIS). The software/hardware components of an EMIS are discussed more in Section 1.2 on the 'data layer'.

The energy productivity applications in Figure 1.2 are summarised below. Some are discussed in more detail in Section 4:

- **Monthly Data Analytics**: Energy bill analytics provides information transparency for tracking the aggregate impact of business sustainability initiatives at monthly or annual intervals. For example, normalised energy tracking over a 10-year period, using the NABERS rating system, has helped building owners in Australia reduce their energy consumption by an average of 30-40%.
- **Energy Information Systems**: Real-time energy (and sub) meter data collection allows more fine-grained analysis of energy trends. These analytics can identify energy consuming equipment and provide energy-consumption baselines to measure the benefits from investing in energy saving activities. Kramer *et al.* (2020) found that the median annual energy savings across a large cohort of buildings was around 3%.
- **Equipment fault detection and diagnosis (FDD)**: By combining sensor data, heating, ventilation, and air-conditioning (HVAC) equipment data and energy meter data, it is possible to get a more detailed understanding of why energy consumption is higher than necessary. This can be used to get insights into how to reduce energy consumption. Across 1,500 buildings in North America, Kramer *et al.* (2020) and Crowe *et al.* (2020) found median annual energy savings of ~9% with a median simple payback time of 1.7 years. FDD derived insights will typically require manual implementation.

- **Automated System Optimisation** (including Model Predictive Control): The NSW Office of Environment and Heritage (2015) describes several advanced HVAC control strategies. Each has the potential for significant energy savings. These automated control strategies can override static control set-points with more dynamic seasonal (or even hourly) set-points, or strategies that take advantage of dynamic price and weather forecasts. Despite energy savings of up to 40%, the opportunity of this technology has not yet been widely exploited. This is at least partly due to fears of automated controls creating unintended or unsupervised consequences.
- **Grid Integrated Demand Flexibility**: Beyond energy efficiency actions in single buildings, the connectivity obtained from an EMIS enables a portfolio of assets to be managed in response to electricity market signals. For example, the Energy Queensland 'Broad Based' flexible demand program connected over 136,000 air conditioners, providing up to 150MW of diversified load under control, during peak demand events, at around 20% of the cost of batteries (Brinsmead *et al.*, 2021).

Smart meters are an important component of these applications, enabling more sophisticated energy pricing and user awareness. However, metering alone is rarely enough to understand a building's energy consumption properly and to drive performance improvements. Consequently, metering should be viewed as just one part of an integrated EMIS.

1.2 The 'Data Layer'

Core to the success of smart buildings is access to data. Data can be exchanged locally, between devices on-premises, using various LAN technology options. However, data accessibility (for potential users) is vastly improved by using cloud technology. The cloud enables a wider range of both on and off-premises data sources to be analysed together. It also enables information to be efficiently distributed to relevant people via remote personal computers and mobile devices.

The generalised digital infrastructure, that Annex 81 considers suitable for implementing data-driven smart-building solutions, is illustrated in Figure 1.3. It identifies a number of 'layers', in the software/hardware stack, that combine to create a highly flexible digital infrastructure, that gives the building owner control over their digital resources, and access to 3rd party software services.

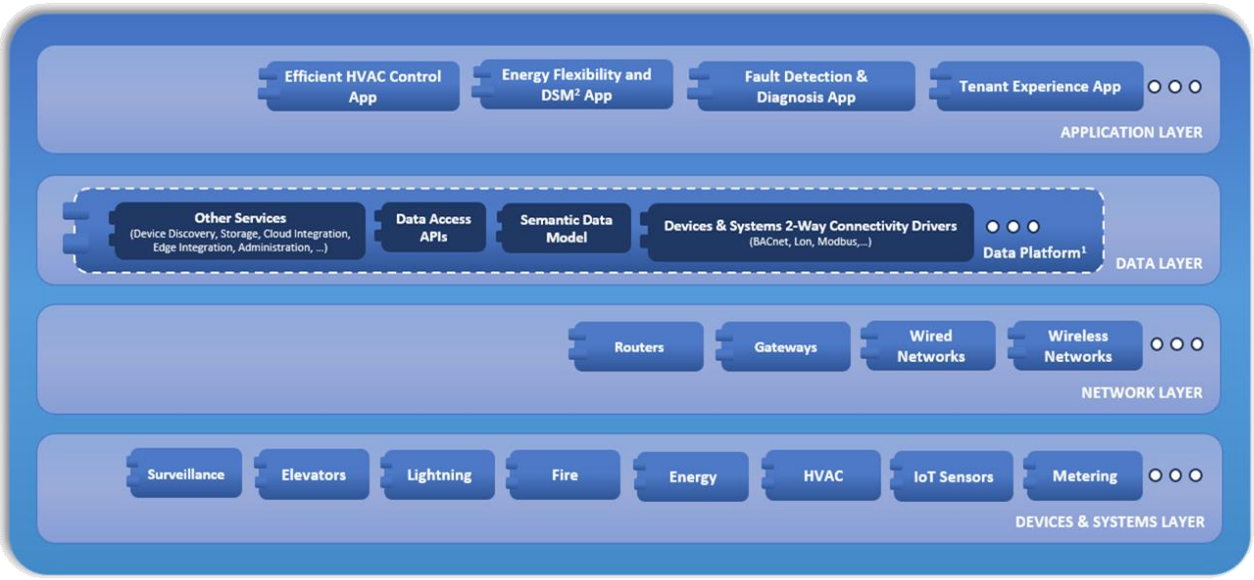

Figure 1.3: The data layer in the digital infrastructure stack.

In the '**device & systems layer**' relevant data sources, from all the equipment and sensors in the building, communicate operational data to an on-premises controller (e.g. building management system (BMS), energy management system (EMS) etc) or data acquisition server. This enables staff to view, monitor and optimise building operations. This local communication is done via local wired or wireless protocols.

In the '**network layer**' data is collected on a local server and/or relevant gateway/hub devices and transmitted to a central cloud data platform (the data layer). Communication can be via a range of wide area communications technologies, including fibre, cable or wireless. This backhaul communications capability from the building may be dedicated to (i) the device (e.g. in IoT applications), (ii) to the broader suite of building services (dedicated building services network (BSN)), or (iii) integrated with other communications services (such as internet, telephone, television), through an integrated communications network (ICN). Much of the cyber security requirements of smart buildings are dealt with in the network layer.

Irrespective of the data source and network layer technology, the role of the '**data layer**' is to (i) consolidate the data in common formats, (ii) provide standardised interfaces to data sources and application software, (iii) provide structured data storage and (iv) make the data accessible to each of the deployed software services in the application layer. The data layer takes the form of a cloud-based data platform.

The '**application layer**' is hypothesized to be somewhat analogous to the 'App Store' on a mobile device. The building owner would simply download their preferred App, and the software would self-configure to deliver the desired service. This self-configuring functionality involves automatically finding and accessing necessary data to enable it to perform the desired service. The application layer vision has independent third-party App developers creating innovative new Apps, to give building owners lots of choice in the services that they can access (rather than be locked into a single vendor's ecosystem).

The smart buildings industry is technologically behind the consumer mobile device industry, and the vision of the 'Smart Buildings App Store' is yet to be fully realized. However, the data-layer concept and data-platforms are a key enabler of this vision. The data layer reduces the cost and complexity of deploying software applications, at least partly by managing interoperability issues.

Various of these data management concepts are discussed in Section 2. The focus of this report is on the data layer and the application layer.

1.3 A 'Digital-Ready' Building

Industry is working steadily toward the adoption of AI solutions and the vision of data-driven smart buildings. However, scalable cost-effective implementation in buildings can still be challenging.

This task of implementing digital energy productivity strategies, in a given building, can generally be divided into two steps: Step 1 - establishing IT infrastructure and associated data management services (the data-layer) and then Step 2 - deploying data-driven software applications (the applications layer).

Unfortunately, solution providers with innovative software applications for step 2, will often need to combine their software with a data acquisition platform (as a bundled service) to address step 1. This is a significant barrier to market entry for specialist software developers. It can lead to multiple platforms being installed in a building (each for its own application), with the resulting potential for cost duplication and data management conflicts.

Separating out the delivery of IT infrastructure, connectivity and the data-layer (step 1), from the delivery of desired data-analytics applications (step 2), as illustrated in Figure 1.4, would be an important step forward for the industry. It would allow (i) a more agile approach to application deployment, (ii) more sophisticated data management practices, (iii) greater competition, (iv) more innovation, and (v) a more diverse range of use cases than is currently encountered in practice.

In this context, industry identified the critical need for buildings to be ‘digital ready’. A ‘digital ready’ building was seen as one that achieves certain minimum standard levels of connectivity and data management capability, sufficient to enable easy deployment of modern energy productivity software-services.

Figure 1.4 illustrates the two-step journey, highlighting the barriers that are encountered, predominantly in the first step of establishing IT infrastructure and data management services. Figure 1.4 further highlights the consequent need to establish some concept of (and guidance for achieving) ‘digital ready’. The attributes and features of ‘digital ready’ would ideally provide a stand-alone target to guide the first step of the digitalisation journey for a building.

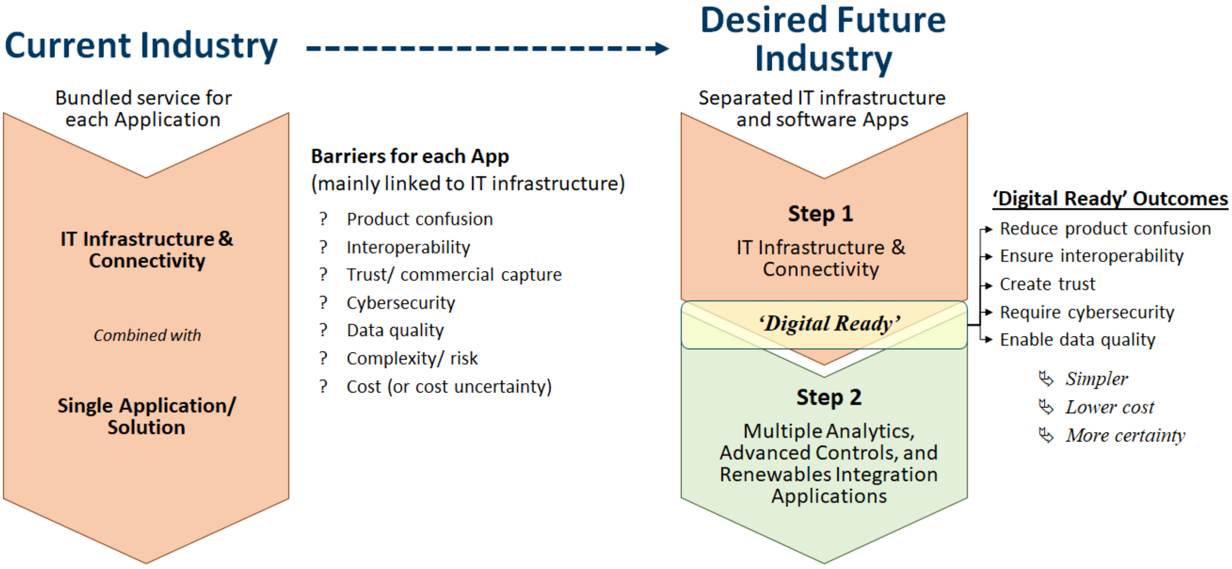

Figure 1.4: The two step journey for deployment of data-driven services (adapted from Trianni *et al.,* 2022), and the benefit of an intermediate ‘digital ready’ landing point.

2. Data Management and Interoperability

Focussing on the 'data-layer' of a smart building, Annex 81 research identified key considerations that are involved in achieving 'digital readiness' in a building. The research particularly considered aspects of data management and interoperability.

Virtually all studies on the barriers to digitalisation point out the significance of interoperability issues and the need for data standards to help overcome them. They point out that interoperability issues relate to both device-level communications and to the level of informational/semantic context attached to data.

Device (communications) interoperability barriers occur when the communication protocols used by one manufacturer's devices are proprietary and therefore unable to talk with the devices from other manufacturers. This makes it difficult and expensive to integrate hardware components from different manufacturers into a coherent operating system for the building. This can also lead to vendor lock-in and high on-going service costs. BACnet (https://bacnet.org/) was introduced as an open communications protocol to address this issue. BACnet is both an international (ISO) and ANSI standard. It is maintained by ASHRAE. Unfortunately, the implementation of BACnet is not always uniform, and interoperability issues can still exist.

Analytics (informational/semantic) interoperability barriers occur when the data being collected from devices comes without any contextual information (metadata) that could give meaning to the data. Important contextual information includes the source and type of data, and the interrelationships between the data source and the features/objects in the building. This contextual information is required to make data 'machine readable', such that software can be automated and can apply logical reasoning to the data that it is processing.

2.1 The FAIR Data Principles

At a philosophical level the building owner can address interoperability issues by complying with the FAIR data principles. That is, data is most useful when it is Findable, Accessible, Interoperable and Reuseable (FAIR). These FAIR data principles are summarised in Figure 2.1.

Box 2 | The FAIR Guiding Principles

To be Findable:
F1. (meta)data are assigned a globally unique and persistent identifier
F2. data are described with rich metadata (defined by R1 below)
F3. metadata clearly and explicitly include the identifier of the data it describes
F4. (meta)data are registered or indexed in a searchable resource

To be Accessible:
A1. (meta)data are retrievable by their identifier using a standardized communications protocol
A1.1 the protocol is open, free, and universally implementable
A1.2 the protocol allows for an authentication and authorization procedure, where necessary
A2. metadata are accessible, even when the data are no longer available

To be Interoperable:
I1. (meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation.
I2. (meta)data use vocabularies that follow FAIR principles
I3. (meta)data include qualified references to other (meta)data

To be Reusable:
R1. meta(data) are richly described with a plurality of accurate and relevant attributes
R1.1. (meta)data are released with a clear and accessible data usage license
R1.2. (meta)data are associated with detailed provenance
R1.3. (meta)data meet domain-relevant community standards

Figure 2.1: The FAIR guiding principles (Source: Wilkinson et al, 2016).

While various sensible constraints may make this difficult to achieve in all circumstances, the FAIR data principles should be the building-owner's aspirational objective, for best practice data collection and data management.

2.2 Metadata and Metadata Management

There is a vast amount of data that can be collected in buildings. To collect and manage this data, it is necessary to think about how that data will be identified, organized, and consumed by downstream data-driven applications. This can be accomplished through the use of metadata – "data about data" – which encodes the salient properties of data, including their provenance (how the data was produced and managed) and their context (where the data comes from and how it relates to the building).

Metadata provides meaning to data. It is a key facet of the FAIR data principles.

Metadata schemas are organisational structures for assigning metadata information to data sources. Among other features, they define:

- how data sources should be labelled or catalogued.
- how the associations between data sources should be represented.
- what attributes and properties can or must be attached to data sources.
- how data sources relate to descriptions of the building and its assets.
- the engineering units and enumeration definitions for the data itself.

Metadata schemas standardise what information should be captured, and in what format. They provide a standardised structure for storing data that is independent of the choice of vendor or protocol, architecture and composition of building, or choice of data-driven consumers and processes. This provides the ability to (semi-)automate installation, configuration, and operation of building software applications, that deliver data-driven controls and analytics.

While metadata schemas provide the general framework for organising information about a given building, the schema is not, in itself, the information about any given building. The actual metadata about an individual building is contained in a *metadata model*. Models are the digital representations of information about a specific building. Figure 2.2 illustrates how a building's metadata model provides the digital interface and relationship mapping between common subsystems (HVAC, lighting, electrical, and plumbing) in a building.

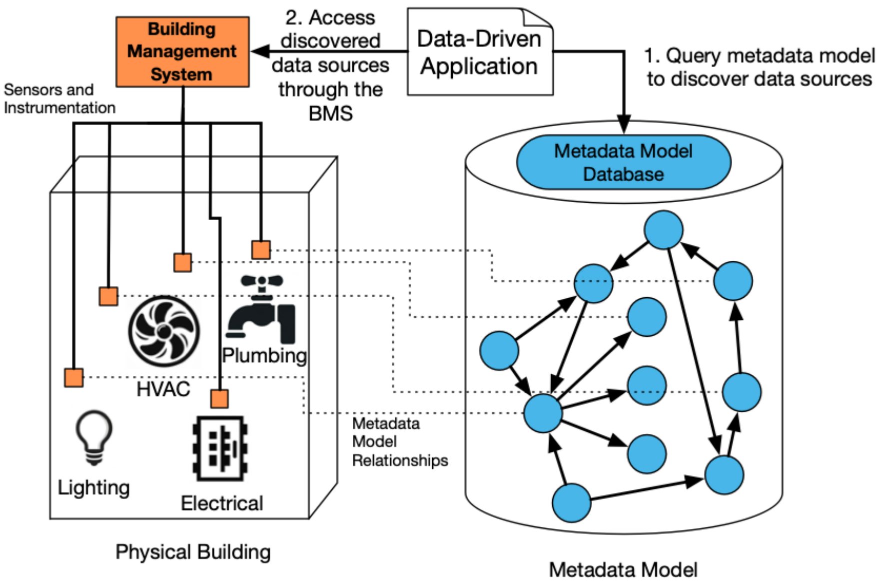

Figure 2.2: Representation of how a metadata model relates to and models the building, its subsystems, and its data sources.

The metadata model is a logically separate entity, typically stored in a database (e.g. a graph database, or relational database), which contains references to the components of those subsystems and their respective data-sources. Software applications (Apps) execute queries against the metadata model to discover and retrieve important details and configurations necessary for processing data.

Ontologies are specific kinds of schemas which go beyond defining possible terms, attributes, and relationships by imposing additional rules and axioms that can ensure the consistent communication of *semantic* information. Ontologies additionally ensure that such metadata has human- and machine-interpretable meaning (i.e. it has *semantics*). Ontologies support an important operation called *validation*. The validation process takes a metadata model as an input and ensures that it obeys all of the rules, constraints, axioms and other requirements defined by the ontology.

Ontologies are commonly, but not necessarily, communicated as graphs using the Resource Description Framework (RDF) W3C standard. RDF ontologies can be expressed in one of several languages, including OWL (Web Ontology Language) and SHACL (SHApes Constraint Language).

2.2.1 Comparing metadata schemas

Different approaches have been taken to the development of metadata schemas for data-driven smart buildings, exhibiting different preferences and the various needs of different use-cases.

When deciding to adopt a metadata schema, we recommend considering the following characteristics of the different schemas available:

1. **Structure of the models that will be created**: The structure of the model determines what questions can be answered through queries against the model. For example, while one can order and filter tabular data by the characteristics contained within, it is more difficult to inquire about relationships between the entities in a tabular model. Point naming schemes are simple to store, but they only support very basic string-based lookups. In contrast, graph-based models support richer queries that can relate multiple entities together in a manner more expressive than tabular models. The user must review the benefits, concerns, drawbacks, and advantages of available options relating to relational models, graph models and point labels. The choice of model should be informed by the questions that the data-consumers, the software applications, and other users of the model need to answer for their operation.
2. **Vocabulary organization and completeness and strictness/rigor**: In this context, “vocabulary” is the terminology used for describing different objects, relationships, and concepts relevant to a building. How are concepts organised and defined in the model? Are they generic or specific? Are concepts defined nominally (through labels) or structurally (through properties)? A detailed vocabulary helps to drive consistent representations but may reduce freedom to describe non-standard scenarios and may be onerous to implement.
3. **Alignment with other metadata schemas**: It may be useful to use more than one schema to cover different use cases and different aspects of the building. This can take advantage of the respective strengths of different schemas (rather than seeking to find a “universal schema”). Consequently, it is important to consider the ways in which metadata schemas may align with one another.

In addition to the technical characteristics of the schema, above, there are a range of implementation considerations that may impact on the viability of a given schema, including:

1. **Impact on smart building software architecture**: How is metadata stored and accessed by software processes in the building? For example, do these processes access a metadata model through a database service, or through another method? How does incorporating a specific metadata schema influence the development, deployment, and management of data-driven processes in the building?

2. **Required tooling / software support / expertise**: do metadata models need proprietary software? What features are required from supporting data platforms? What does this mean for its deployment in a building? Is the schema commercially supported? How can models created using the schema be used by the BMS, and relevant data platforms?
3. **Creation / bootstrapping /maintenance**: Engineering time is generally required to create a model for a building. It is important to consider how models get built and maintained. Can model development and management be done in an automated way, or does it require manual curation? Who owns the metadata model? When changes are made in the building, how does the model get updated and by whom?

The following metadata schemas were surveyed in the Annex 81 report “Survey of metadata schemas for data-driven smart buildings” (Fierro and Pauwels, 2022): Project Haystack, Brick, RealEstateCore (REC), Building Topology Ontology (BOT), Smart Applications REFerence Ontology (SAREF4BLDG), Semantic Sensor Network Ontology (SSN/SOSA), and Google Digital Buildings (DBO). These schemas differ primarily in how data models are created and how they support data processing and data discovery in smart buildings (Table 2.1).

Table 2.1: Overview of metadata schemas and their model structure.

Metadata Schema	Naming Convention	Tags	Relational	Graph	RDF Ontology
Haystack	No	Yes	No	Yes	No
Brick	No	Yes	No	Yes	Yes
RealEstateCore	No	No	No	Yes	Yes
BOT	No	No	No	Yes	Yes
SAREF4BLDG	No	No	No	Yes	Yes
SSN/SOSA	No	No	No	Yes	Yes
Google Digital Buildings	Yes	No	No	Yes	Yes[2]

Several schemas — Project Haystack, Brick, RealEstateCore and Google Digital Buildings — deal directly with the management and organisation of telemetry information in the building. Project Haystack and Google Digital Buildings explicitly define the format of the data and how it is accessed. Brick and RealEstateCore define more generic structures which can be incorporated into a variety of APIs and software platforms.

Other schemas — BOT and SAREF4BLDG — provide more contextual information about the building which can assist software applications to find relevant data. They typically focus more on asset management rather than telemetry data. As a result, these metadata schemas are much closer to the architecture and engineering construction domain and the processing of BIM information. Conversely, SSN/SOSA provides all needed mechanisms to represent sensor data and actuator data on a large and detailed scale. It leaves the representation of actual building data to other ontologies like Brick, BOT, and SAREF.

Among the schemas, there are a variety of perspectives of what in the building should be modelled, and there are differences in the consistency and specificity of those perspectives.

Brick and Project Haystack are able tp model many common building subsystems including HVAC, lighting, and electrical systems. Project Haystack’s tagging model affords a great deal of flexibility in describing these systems at the cost of consistency across Haystack models. In contrast, Brick prescribes more of the model structure in exchange for a consistent modelling and querying experience for the consumer of the model. Google Digital Buildings focuses primarily on collections of data coming out of the building, rather than the topology and composition of the building subsystems. RealEstateCore is similar to Brick, but focuses more on property management aspects. It includes a shallower hierarchy of equipment and data source types.

[2] The Google Digital Buildings metadata schema defines an OWL ontology export but it is not the intended mode of interaction, and does not support all features of the metadata schema

Finally, BOT tends to focus much more on asset management and description of the building itself, with much less focus on HVAC systems or their telemetric data logs.

Generally, we can recognize a spectrum of schemas, from very flexible approaches (on the left in Figure 2.3) towards more rigid and formally defined approaches (on the right in Figure 2.3).

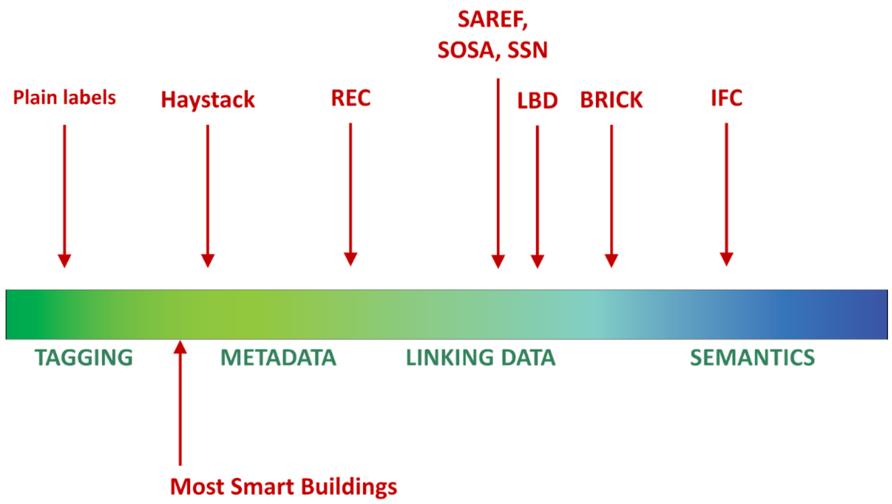

Figure 2.3: A spectrum of building data representation from more flexible and ad-hoc (leftmost) to more formal and semantically defined (rightmost); plus the estimated location on that scale for several existing metadata schemas.

Despite the diversity of approaches and stakeholders for each metadata schema, there is a growing desire to ensure unity and alignment between the various groups. More than one schema can be used to take advantage of respective strengths in different use cases (rather than seeking to find a "universal schema"). We predict, hope, and recommend that future editions of metadata schemas will focus more on complementing each other through reductions in scope, rather than expanding the modelling scope to try to compete on all the different perspectives of data-driven buildings.

We also see RDF-based metadata schemas emerging as the dominant modelling approach. These demonstrate the highest degrees of interoperability and reusability compared to other proprietary models.

2.2.2 Semantic Sufficiency

One of the key challenges in adopting semantic metadata is how to create and validate the metadata model for a building (*validation* is the process by which a metadata model is checked against the rules, axioms, constraints, and other requirements defined by an ontology).

Because fully automated metadata model creation has not yet been developed, most deployments still require some manual effort to create the metadata model from existing sources of data (see Fierro and Pauwels, 2022 for more details). Without some guiding principle for what parts of the model to prioritize, model authors are left to either model everything (which can be cost-prohibitive) or guess at what metadata will be required by downstream analyses, controls, and other data consuming processes. The lack of such a principle means it is possible to create models which are valid with respect to the ontology, but do not actually contain enough metadata to support applications.

To address the lack of such a principle, Fierro *et al.* (2022) introduced *semantic sufficiency*, a practical approach to creating and evaluating "complete" semantic metadata models. Semantic sufficiency pulls application-level requirements on metadata into the validation process. Specifically, the semantic sufficiency principle holds that a model is "complete" when it contains sufficient metadata to support a desired suite of applications. While straightforward at first glance, this principle exposes two important features enabled by semantic metadata. First, semantic metadata makes it possible to precisely express the configuration information required by a software application using the metadata schema. Second, semantic metadata makes it possible to *verify* that a given model of a building contains the correct (or "sufficient") metadata to support a desired suite of applications.

Consider the workflow illustrated in Figure 2.4. Model authors are given a point list (A), usually from some standard or other control specification. The point list contains the informal names of the sensors, actuators, and other inputs and outputs required by some data-driven application. In Figure 2.4, the point list given is from the ASHRAE Guideline 36 document for high-performance sequences of operations for common HVAC systems.

Such a point list can be expressed as *shapes*, which are functions that validate part of a model (e.g., a particular piece of equipment) against the metadata requirements for a given application (B). Shapes allow metadata models (C) to be *validated* against a family of application specifications. The output of validation is a report (D) which tells the model authors (E) what metadata needs to be added or corrected to make the model *semantically sufficient*. The model is semantically sufficient if it contains all of the metadata required for relevant metadata-aware software applications to configure themselves and execute.

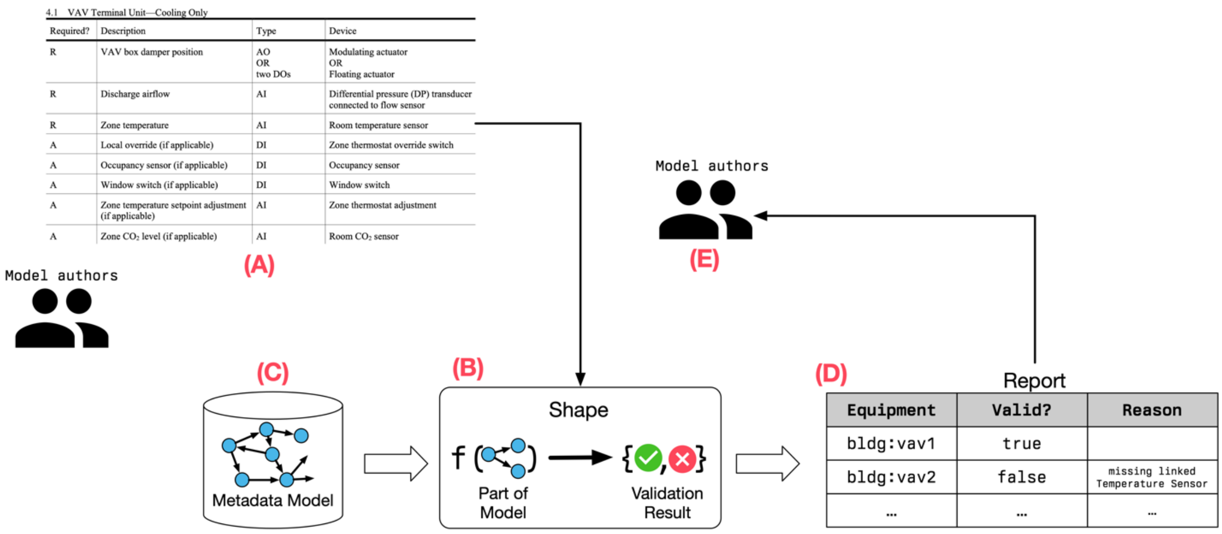

Figure 2.4: Illustration of how semantic sufficiency guides the creation of metadata models.

Currently, this semantic sufficiency information is almost non-existent, or at least not explicitly provided. However, in future we would expect data requirements lists to be provided by software application providers, so that building owners and their contractors can ascertain what information is missing for successful deployment, before purchasing a service.

This is an important step for the future of the data-driven software services industry, as knowledge of the required sensors, actuators, and other I/O points allows stakeholders to determine the business case for adopting the application. That is, by reading the metadata requirements of an application, the building owner can determine the capital cost of buying the required sensors and equipment (if not already there), and they can determine the cost for making those data sources available. These costs can then be compared with the expected financial benefits of adopting the software application, to make the business case for investment with adequate certainty.

2.3 Governance of Data

Just because data can be collected, does not mean that it can be shared. Care should be taken to ensure that permission has been granted prior to using data.

2.3.1 Licence to use commercial data

Often this is obtained through a license from the data owner. However, the concept of the data owner is not always obvious.

It is common for people and businesses to refer to data as if it is something that can be owned. For example, individuals and businesses commonly refer to ‘my data’ or ‘our data’. However, in general, there are no property rights in individual points of data. Therefore, data is not normally owned.

Instead, deliberate collection and curation of data as a *data-set* can be viewed as a ‘creative work’ subject to copyright law. Various actors may have some claim to helping ‘make’ a data-set, with the resulting possibility of having some rights over the intellectual property. The maker will probably be the entity who made the commercial decision to collect the data and made the commercial investment in carrying out the collection and curation of the data-set.

Given that the building owner ultimately pays for all the services, and needs the ability to competitively source providers at regular intervals, it is generally assumed that data should belong to the building owner. This may not be the case, and (irrespective of legal rights) data has a practical tendency to find its way to the service provider and end up inaccessible to the building owner. Indeed, the uplift of data to access-controlled external IT systems can sometimes be used as a commercial tool (as part of a service provider’s business model) for ensuring that the building owner retains their services.

2.3.2 Basis for using personal data and data controls

The General Data Protection Regulation (GDPR) (https://gdpr-info.eu/) regulates data protection and privacy in Europe. It has also been adopted, in full or part, in various other jurisdictions. The GDPR defines personal data as any information that relates to an identified or identifiable living individual.

Most energy productivity applications in commercial buildings will use base-building data sources that relate to the operation of the whole building. As this data relates to the aggregate (rather than individual) needs of commercial building occupants, it is typically not considered to be personal data relating to an individual.

However, some applications could potentially utilise occupant data which is personal. For example, occupant movement data can be used as an input to drive allocation of energy consuming HVAC services. Occupants in the building may also wish to interact with building services using Apps on their mobile phone (e.g. to improve thermal comfort conditions, make meeting room bookings, or access other resources etc), which also has the potential to lead to the collection of personal data (e.g. email addresses, MAC addresses etc).

When using personal data, the GDPR requires that there be (i) a legal “basis” for processing the data, (ii) adherence to general data processing rules of transparency and fairness, and (iii) appropriate technical and organisational safeguards in place to ensure the security of the personal data. The GDPR takes a risk-based approach, where companies/organisations that process personal data are encouraged to implement protective measures corresponding to the level of risk of their data processing activities.

The six legal bases for processing personal data that are recognised by the GDPR (Article 6(1)) include:

1. The data subject has given consent
2. Performance of a contract, to which the data subject is party
3. Compliance with a legal obligation
4. Protecting the ‘vital interests’ of the data subject
5. Public interest or acting under official public authority
6. ‘Legitimate interests’

The Five Safes Framework can be used to identify protective measures for safeguarding personal data. The data sharing principles of this framework are illustrated in Figure 2.5 below.

Each of the Principles can be considered as a focus area, where the stringency of the required control mechanisms (risk management choices) can be adjusted to achieve an appropriate balance between openness and the level of sensitivity of the data being shared.

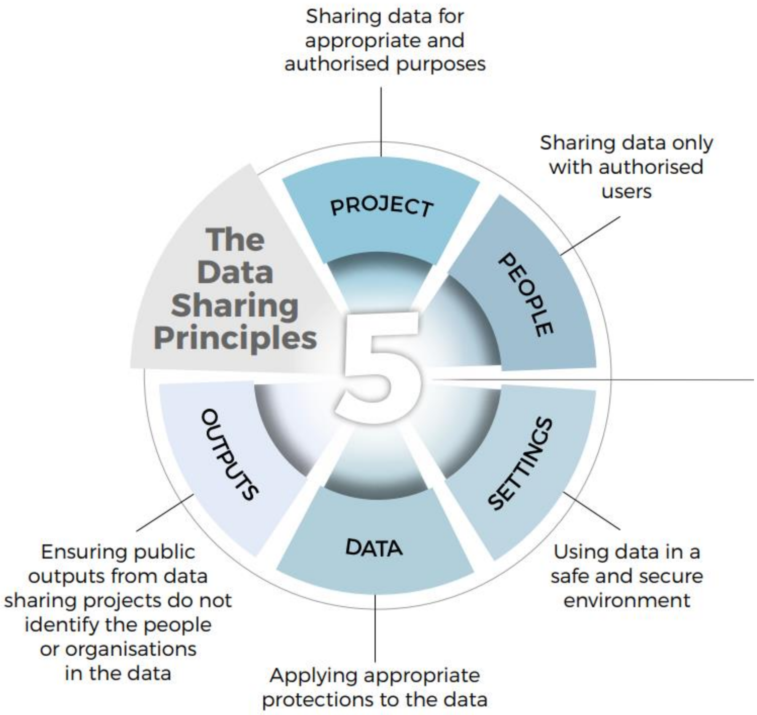

Figure 2.5: Principles for Sharing Data Safely (Source: Commonwealth of Australia, 2019).

2.4 Choosing a Data Platform

The data-layer (introduced in Section 1.2) – which enshrines relevant interoperability and data governance considerations (discussed in Sections 2.1, 2.2 and 2.3) – is ultimately implemented as a data platform.

Data platforms provide the cloud software layer for distributing data to where it is needed. The data platform is (for digitalisation of buildings) analogous, at least partly, to what a computer operating-system is for a personal computer; guiding computational workflows and exchanging data to/from storage. Importantly, the data platform consolidates data from disparate sources in one location and uses relevant data standards to provide a coherent, harmonised structure for the data.

In different contexts/applications the data platform could be called an IoT platform, an Energy Management Information System (EMIS) or Distributed Energy Resource Management System (DERMS).

The data platform provides an intermediating role between data collection and data-driven services (software applications). The assembly of consistent yet individually curated datasets, on a platform, enables applications software to be cost effectively developed and deployed. Without this enabling aggregation, individual software application developers would need to engage with each individual data owner, potentially having to develop tailored applications based on the structure and semantics of each source of data.

Consequently, the platform plays a key role in brokering the relationship between data providers and software application developers who use the data to deliver value back to the providers. This brokerage entails:

- Setting consistent standards for data uploaded or deposited to the platform
- Qualifying/validating/authorising the applications that interact with the data on the platform

2.4.1 Strategic data-platform procurement consideration

Given the role of the data platform, described above, it is clear that data platforms can (at best) facilitate desirable access to data but (at worst) can frustrate access to data and create a position of market power for the platform owner. Consequently, acquisition of a data platform is a significant strategic decision for the building owner. Key considerations for the building owner include

- Data Sovereignty: By collecting data and storing data on behalf of building owners, a data platform owner could potentially gain significant visibility of confidential or sensitive data, and/or be able to use the data to provide services to others. Indeed, the business model of some IT platforms, in some other industry sectors, is to provide services for free on the condition that the collected data can be harvested to generate separate revenue streams for the platform owner.
- Vendor lock in: Once data is stored on an external provider's data platform, it may be difficult to recover that data if there is reason to change provider. This potential (to lose historical data) creates a disincentive to change provider, stifling competition and innovation. Similarly, so-called 'network effects' have the potential to create natural monopolies for platform providers. The more a platform is adopted by users the more useful it becomes and the harder it is for others to compete.

Options for building owners include

1. The building owner establishes a private data warehouse for capturing, storing and managing data on the operation of their buildings. Data is stored on the building owner's servers and separately distributed to service providers by the building owner:
   - ➪ In this scenario, the cost of developing the data platform is high, but the building owner maintains full control and in-house capability to enable more tailored/bespoke services.
2. The building owner utilizes a third-party data platform service to collect and manage their data, as a separate service to any analytics provider(s) that the building owner may subsequently use:
   - ➪ In this scenario, the cost of developing the data platform is reduced compared with developing a bespoke data-warehouse. To the extent that the data platform is independent from analytics services, and provides the building owner with tools for accessing and self-managing their data, the data platform can provide access to a wide variety of third-party services.
3. Building owner obtains data platform services bundled up inside relevant software services.
   - ➪ In this scenario, the building owner does not explicitly pay for a data platform. Instead, the platform is installed somewhat inadvertently. This potentially limits access to data (loss of data sovereignty) and limits the ability to reuse data for other services (vendor lock in).

While the property industry has generally been slower than the broader IT industry to consider many of these issues, there are various highly capable companies offering data platform services via a Platform-as-a-Service (PaaS) business model.

2.4.2 Data Platform Functionalities

Key capabilities of a data platform include:

A. Building Onboarding and Data-Source Connection: A building services contractor must be able to connect the data platform to, and ingest data from, the various on-premises data sources in a way that recognises context (ie metadata information that can relate the data source to features of the building). These data platform functionalities include;

- *Building registration wizards*: These wizards are used for initial registration/ configuration/ partitioning of a new building on the data platform, and for describing the features of the building. The features of the building, entered into the system, can then be used as tags for ascribing meaning to data sources streaming into the platform. Ideally the building registration wizard will support the creation of a building model based on a recognised industry standard metadata schema.
- *Device communication protocols*: The platform should be able to ingest data from a wide variety of devices using common communications protocols such as BACnet, Modbus, and MQTT. It should also be able to ingest data through APIs and perform scheduled FTPS ingestions of Comma Separated Values (CSV) files.

- *Data-source connection*: The platform should provide means for a building services contractor to find, authenticate and connect to data-sources.

B. Data Storage and Retrieval: The data platform should enable people and machines to find and retrieve data from storage in a way that facilitates data-processing and avoids data leakage. These data platform functionalities include;

- *Data cleaning*: A range of tools should be available for processing incoming data to ensure data quality including (i) detection of anomalies and stale data and (ii) data interpolation to fill gaps and unify timestamps etc.
- *Time series database*: The platform will store time-stamped data so that trends in the data can be identified.
- *Metadata store* (e.g. graph database): to process logical queries for finding data sources from the timeseries database, on request by software applications. This store takes advantage of the metadata schema to support software and data reuseability.
- *Data access permissioning system*: Data should be containerised in a way that provides data 'ownership' for the designated data-controller organisation. The data-controller organisation would appoint an administrator responsible for maintaining data sovereignty for the organisation. From there, only authorised people and software applications should be able to access data, through a permissioning system supervised by the administrator. The platform should permit users to access specific data (not just all or nothing), at different role-based levels of access (e.g. read or write).
- *Data download*: Time series data should be able to be downloaded by the permitted user as a csv file, and be streamed to permitted third party software applications via APIs.

C. Data Utilisation and User Support: The data platform should provide basic support features (beyond just data-management/ data-access, as described in B above) that help users to deliver value adding data-driven software services.

- *Basic visualisations and alerts*: The user should be able to view trendlines for timeseries data and thereby manually explore possible cause and effect relationships between different data streams. The user should be able to set alerts to reflect their preferred alert thresholds.
- *Compute resources and output signals*: Algorithms will ideally be able to (optionally) process data on-platform (as "Applications"), utilising Platform-as-a-Service (PaaS) compute resources. The results/outputs from these data-processing algorithms should be able to be automatically sent to remote devices, as informational alerts and/or supervisory control signals.
- *Application Marketplace and Third-Party Data*: These feature enables building managers to extend the data platform's built-in capabilities through the ability to browse available third-party data-sources and/or install third-party, data-driven, ready-to-use applications on the platform. A software development kit (SDK) would ideally be available for third party developers, so that independent software developers can be contracted to build customised applications.

A review was conducted of available data platforms in 2022. The aim of the review was to gain an indicative understanding of the extent to which the desirable features of data platforms are readily available in the market. The review involved collecting responses from platform owners to a questionnaire/survey covering 11 thematic areas:

1. Governance
2. Data access and security
3. Data upload/building onboarding
4. Data capture
5. Data storage
6. On-platform programming
7. Data and application code recovery
8. Output signals and control
9. Applications marketplace
10. Screens and visualization
11. Platform development

The questions were both of a quantitative and qualitative nature. Questions included both (i) closed yes/no or multiple-choice answer questions, and (ii) open text-based questions, with no limits on the length of the answer. Responses were received from 12 data platforms, covering both not-for-profit/government platforms (6) and commercial platforms (6).

Some findings from the survey include:

- Five out of the 12 platforms did not use any external cloud hosting services, for 1 it was optional, 2 used Amazon Web Services and 3 used Azure.
- 9 out of the 12 platforms gave clients discretion over access to their data, and 2 could be fine-tuned for this possibility. All platforms claimed the ability for the client to make parts of the data (within a building) available to third parties. 10 out of the 12 platforms could provide different tiers of access based on role, both internally (within the data client organisation) and externally for authorised third parties.
- Platforms had connectors for the common open communications protocols (e.g. BACnet, Modbus), and various data cleaning functions. APIs were provided in 10 out of the 12 platforms, to assist with data export to external platforms.
- A structured schema (such as Brick), that enables data to be linked to physical spaces and systems within the building, was used by 7 of the 12 platforms. There was no consistency across the platforms regarding the programming languages used to query the database.
- An Applications marketplace (including means for 3rd party providers to list/advertise their software applications to data clients) was provided in 4 out of 12 platforms and it was under construction in 2 platforms. One platform had a payment gateway for charging App usage fees. One platform hosted an open github community, but did not provide a marketplace.
- Six out of the 12 platforms were capable of dispatching high level interface outputs, for cloud-based supervisory control of building mechanical systems.

The survey highlights growing technical maturity in the market with most data platforms providing sophisticated data capture and data management capability. A significant point of difference relates to the availability of data sharing capabilities that support third-party application developers. These points of difference include (but not limited to) availability of an application marketplace and use of common programming languages for querying the database. Presumably, this partly reflects differences in adopted commercial business models.

There also appear to be some different perspectives on the future role of data platforms in smart buildings. A number of data platforms have opted not to utilise cloud hosting. And many of the platforms have opted not to target supervisory control services. This may reflect different perspectives on the viability of certain applications, when cyber security is considered.

3. Data Availability and Building Performance KPIs

Benchmarking building operational performance is a critical step in understanding the quality and capability of a building in terms of its energy-efficiency, air quality, and comfort for occupants. This is a multi-criteria assessment typically involving (i) collection of relevant data from sensors and equipment and (ii) using the data to calculate suitable key performance indicators (KPIs). These KPIs provide actionable information that can help to evaluate and track if a building is meeting its objectives.

Annex 81 research investigated the usefulness of available data-driven KPIs, and the availability of data sufficient to calculate them. Given that a good KPI should be accessible, quantifiable, and actionable, the research was structured to address the following three research questions:

Research Qu 1: What are the KPIs used in existing buildings and in energy-related literature?

Research Qu 2: What KPIs can be implemented within the existing infrastructure of current buildings?

Research Qu 3: Which KPIs are important to building industry stakeholders?

The questions and the methodology for answering these questions is indicated in Figure 3.1.

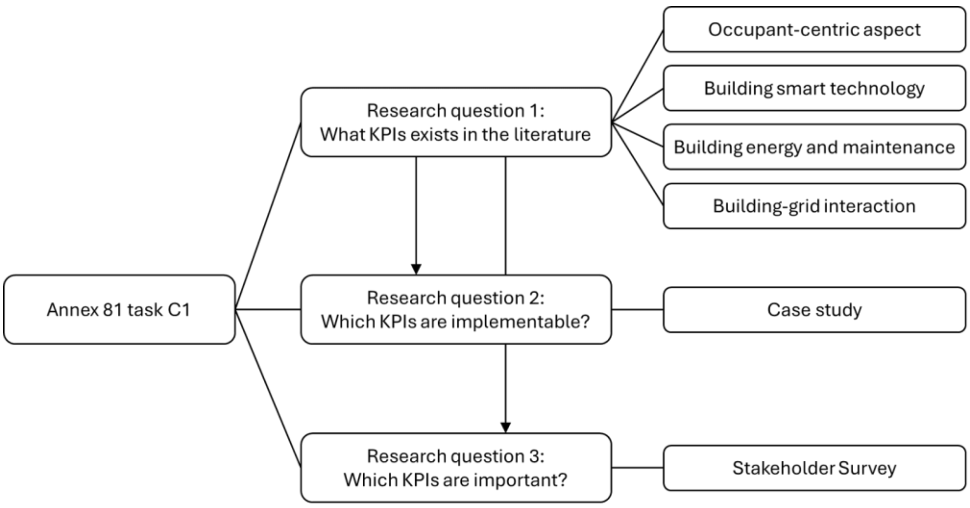

Figure 3.1: Methodology for assessing operational building performance KPIs.

Annex 81 research also investigated data collection issues, predominantly through interviews and surveys.

3.1 Data-Driven Building Assessment KPIs

The literature identified numerous KPIs. These are clustered against four target outcomes/ impact-areas.

Occupant-centric KPIs

Occupants are the primary beneficiaries of building services. Occupants influence the energy performance of buildings and, in-turn, building operations shape the occupants' experience of comfort, productivity, and well-being. KPIs are required to measure these influences. Occupant-centric KPIs were categorised into three main areas: those related to occupants' interaction with building systems, those based on indoor/outdoor environmental parameters, and those related to occupants' subjective feedback.

Drawing from the building life cycle, the stakeholders who are most relevant to occupant-centric KPIs include building designers, occupants, building managers, and building owners. From the perspective of these stakeholders, the review identified 22 thermal KPIs, 11 air quality KPIs, 10 acoustic KPIs, and 17 visual-lighting KPIs. These KPIs quantify the occupants' comfort, health, productivity, and well-being

(Sleiman *et al.*, 2024). Comfort-related KPIs are the most popular KPIs. Dry-bulb air temperature, CO_2, sound level and illuminance are the most required input data for thermal, air quality, acoustic, and visual KPIs, respectively. Although KPI calculation formulas exist, challenges persist due to unclear definitions and a lack of specified sensor/ meter data requirements, particularly on the whole building level. Further work is needed to specify the methodology to compute these occupant-centric KPIs.

Building Smart Technology KPIs

Two aspects of smart building technology were considered: Interoperability and Transfer Learning.

The significance of interoperability testing in achieving seamless integration is widely acknowledged. To address this issue, interoperability testing is required using common specifications and universally accepted quantifiable KPIs. Various methodological approaches exist for interoperability assessment in the smart grid domain (Ginocchi *et al.*, 2020). For example, Ford *et al*. (2007) developed an i-Score methodology to assess the interoperability of networks of systems. This methodology abstracts the systems as an architecture framework that describes how these systems work. Based on the architecture data, it employs graph optimization, and interoperability theory to offer a comprehensive assessment of interoperability. Van Amelsvoort *et al.* (2015) then adapts this i-Score methodology for interoperability testing in the smart grid domain. However, the prevailing practice of devising ad-hoc interoperability testing procedures, without embracing well-structured methodological approaches, can result in issues such as irreproducibility, subpar quality, prolonged development times, and increased costs (Ginocchi *et al.*, 2020). Despite the evident importance of interoperability, progress in initiatives to enhance the current situation is sluggish.

Transfer learning (TL) is a powerful technique in machine learning, where a model trained on a specific task (i.e., source task, or a source building) can be applied to a new task (i.e., target task, or a target building) that shares similarities with the original task, whether that is within the same domain or across different domains. In the context of smart buildings technology, implementing a transfer learning strategy can improve model performance, reduce the model computation time, and lower the cost of deploying smart algorithms. This could be for use cases such as load prediction, occupancy detection, activity recognition, building dynamics, advanced control systems and fault detection and diagnosis. The traditional TL process includes 1) identifying the best source domain (building) using similarity metrics; 2) applying TL solutions; and 3) assessing TL performance.

From the analysis of different applications in the built environment, two different approaches were identified: a semantic approach and a data-based approach. The semantic approach uses features, metadata, and semantics to study the similarities between two buildings, while the data-based approach analyses the datasets available, trying to assess similarities between the source and the target datasets, using both features and time-series data.

The assessment of TL performance requires the definition of several metrics to assess building similarity (i.e., domain similarity) and machine learning performance. These are employed to compute KPIs that quantify TL advantages in terms of performance, speed, data requirements and reliability. A number of KPIs have been introduced by Zhu *et al.* (2023), to quantify the performance of TL for building applications such as jumpstart, transfer ratio, asymptotic performance, time to threshold, performance with fixed number of epochs, performance sensitivity, necessary knowledge amount, and necessary knowledge quality. However, each KPI needs to be contextualized in the framework of the TL application.

By way of example, in the Load Prediction application, several common KPIs were used to evaluate the performance of prediction models (Johra *et al.*, 2023b) and the consequent improvement when a TL framework is implemented. These KPIs include RMSE improvement (Lee and Rhee, 2021), CV-RMSE improvement (Ding *et al.,* 2023) and MAPE improvement (Lu *et al.*, 2021), Moreover, various techniques have been used to assess building similarity, such as Dynamic Time Warping (Peng *et al.*, 2022), Similarity Measurement Index (Lu *et al.*, 2021), Maximum Mean Discrepancy (Li *et al.*, 2022) and Mahalanobis Distance (Jin *et al.*, 2022).

Building Energy Saving and Maintenance KPIs

Energy performance indicators are often integrated into rating and certification systems based on building energy codes and standards. Li *et al.* (2020) summarized the most common energy performance indicators at the building level and introduced a set of system-level KPIs that include four major end-use systems and their eleven subsystems.

Building maintenance encompasses a range of activities aimed at preserving and repairing the functionality, safety, and aesthetics of a building and its components. Maintenance costs can account for up to 65% of annual facility management costs (Hosamo *et al.*, 2022). EN13306:2017 (2017) introduces three types of maintenance: Improvement maintenance, predictive maintenance, and corrective maintenance. Based on these maintenance types and the comprehensive list of maintenance KPIs in EN15341:2019 (2019), the review identified eight categories of KPIs: physical asset management (20 KPIs), information communication technologies (20 KPIs), health safety and environment (22 KPIs), maintenance management (22 KPIs), people competence (20 KPIs), maintenance engineering (19 KPIs), organization and support (30 KPIs), and administration and supply (29 KPIs). Maintenance KPIs relating to Fault Detection and Diagnosis were also identified (Chen *et al.*, 2023), and classified into three further categories: general evaluation metrics for FDD applications (8 KPIs), evaluation metrics for data-driven classification problems (5 KPIs), and statistical significance tests that assist the evaluation of classification problems (5 tests).

Energy Flexibility KPIs

Drawing inspiration from the EU Smart Readiness Indicator (SRI) assessment scheme, a review was also done of KPI's for benchmarking a buildings ability to flexibly manage its energy consumption in response to grid needs. 29 generic KPIs and 48 data-driven KPIs were identified for assessing demand response and building energy flexibility (Li *et al.*, 2023). These KPIs relate to power peak shedding, average power load shedding, peak power/energy rebound, valley filling, load shifting, demand profile reshaping, energy storage capability, demand response energy efficiency, demand response costs/savings, demand response emission/environmental impact, grid interaction, and impact on indoor environment quality. These KPIs usually have low complexity, but most of them (81%) require a baseline (counterfactual energy consumption scenario without demand response) to be calculated. The most popular of these KPIs are related to the energy efficiency of a demand response action, the load shifting capacity (typically from high-price periods to low-price periods), and peak power shedding.

In summary, the literature overview collected 60 occupant-centric KPIs, 40 KPIs for transfer learning, 274 KPIs for building energy and maintenance, and 77 KPIs for building-grid interaction, resulting in a total of 451 KPIs Figure 3.2).

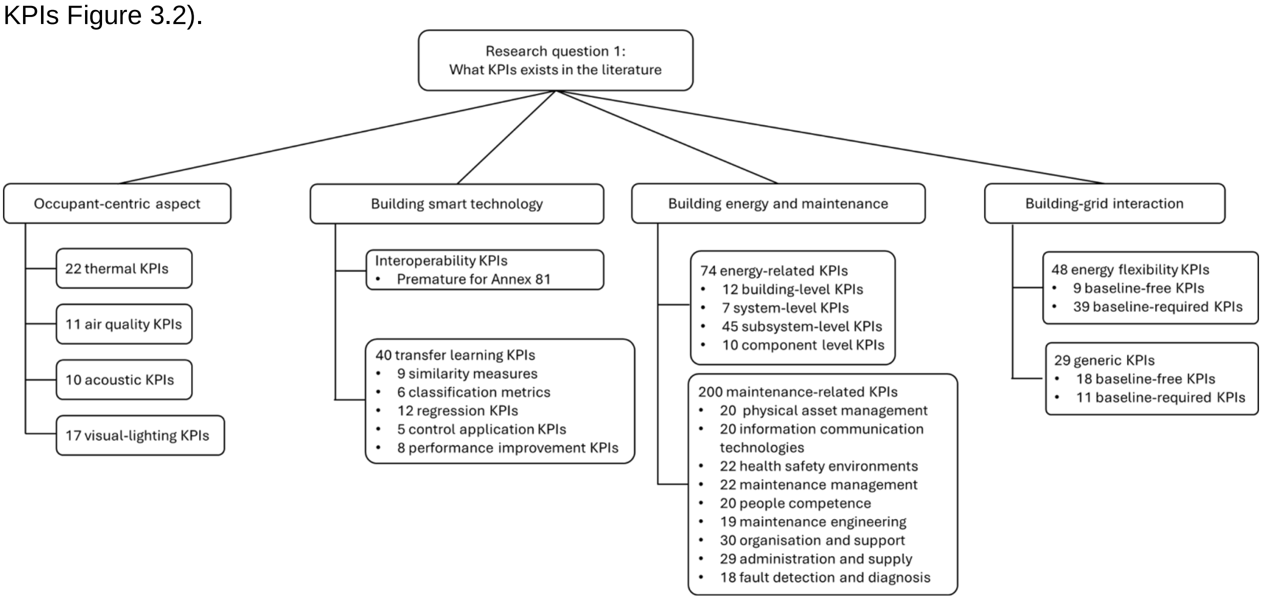

Figure 3.2: Overview of the collected KPIs.

3.1.1 KPIs and stakeholder needs

The popularity of these KPIs in the research community does not necessarily reflect their applicability, desirability and usefulness for industry stakeholders. A survey was conducted, seeking input from stakeholders on essential aspects of building operational performance. The survey was designed based on the proposed KPI framework, incorporating three building performance goals: 1) to improve buildings' energy saving and operation, e.g., energy efficiency, operational cost, environmental impact, and maintenance. 2) to satisfy occupants' needs, e.g., comfort, health, well-being, and convenience, and 3) to satisfy the grid's requirements and provide building-to-grid services, e.g., grid stability and demand response. Each general goal was further subdivided into four sub-performance/technical aspects. The survey employed the Analytic Hierarchy Process to gauge stakeholder opinions on the relative importance of two performance aspects and to calculate their corresponding weights.

A total of 137 stakeholders received the questionnaire, with 65 stakeholders completing the survey (47.4% response rate, predominantly building managers). The results indicate that stakeholders typically prioritize occupants' needs the most, followed by the building's energy efficiency and operation. Stakeholders exhibited the least concern for the grid's requirements. Within the occupants' needs category, occupant health emerged as the most important aspect and sub-aspects like mitigating respiratory disease transmission, followed by comfort. For building operations, stakeholders considered the downtime of the building system as the most critical consideration, while operational cost ranked as the least important. In contrast, for building energy flexibility, all technical aspects held similar importance, encompassing power peak shedding, energy/average power load shedding, peak power/energy rebound, valley filling, load shifting, demand profile reshaping, and energy storage capability. However, the study also unearthed notable variations in priority among individual stakeholders. Specifically, only 52% ranked occupants' needs highest, while a smaller fraction (14%) deemed the grid's requirements their foremost concern (Figure 3.3). This may be caused by many factors, such as stakeholder type, the building functions, policy, and country.

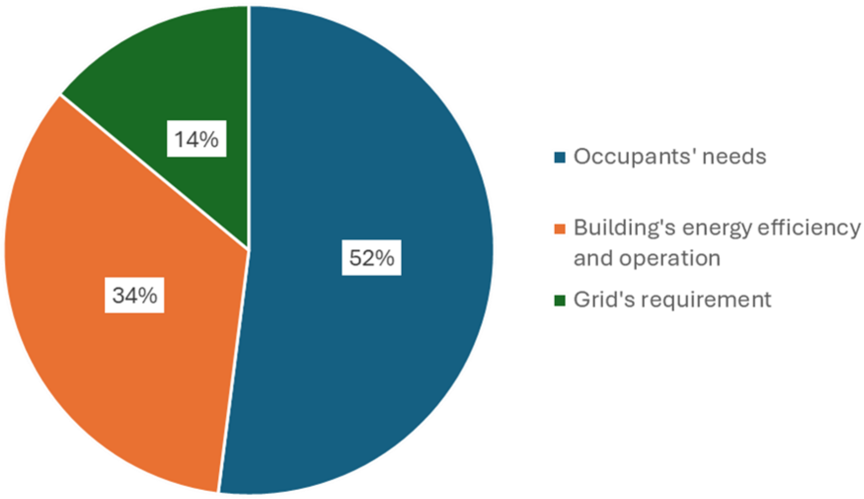

Figure 3.3: Stakeholders priorities relating to different building performance aspects.

3.1.2 KPI calculation feasibility case-studies

The availability of KPIs (and their associated calculation formulas) also does not necessarily reflect the ability to source required data and calculate these KPIs in typical buildings. A comprehensive evaluation was performed to ascertain the feasibility of computing various KPIs across five office buildings (four located in the Netherlands and one in Switzerland). The analysis used historical BMS data and focused particularly on occupant-centric and energy flexibility metrics.

The findings underscore challenges associated with data availability for KPI computations. Thermal comfort KPIs are found to be the most readily calculable among occupant-centric KPIs, while those related to building lighting and acoustics present significant challenges when using BMS data. Similarly, within energy flexibility KPIs, only those dependent on total energy demand are generally calculable. On average, only approximately one-quarter of the collected KPIs could be reliably calculated for the case study buildings (Figure 3.4).

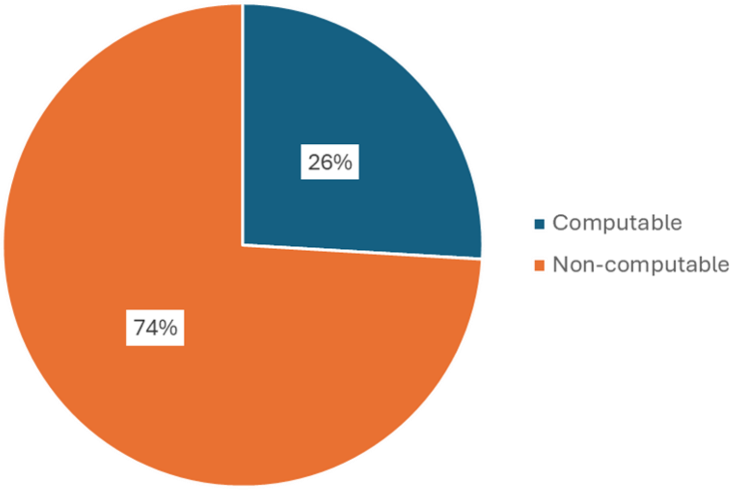

Figure 3.4: Percentage of KPIs that are computable using historical BMS data from the case buildings.

Furthermore, a detailed assessment of six KPIs, namely Predicted Mean Vote (PMV), Predictive Percentage of Dissatisfaction (PPD), Percentage of CO_2 exceeding the threshold (PCO_2), Energy Consumption per square meter (EC), Flexibility Factor (FF), and Load Factor (LF), was conducted to gauge the performance of the case study buildings. While these KPIs can be computed, their definitions lack consideration for the complexity of real-world building scenarios, introducing ambiguity and limiting reliability in calculations.

For example, the PMV index relies on indoor air temperature as an input parameter. Amongst the case-study buildings, one building has forty indoor air temperature sensors distributed in various rooms, while another one has only one indoor air temperature sensor. This variation in the number and placement of indoor air temperature sensors can lead to bias in the PMV calculation when comparing the thermal performance of two buildings. Several key considerations are highlighted:

- Input data quality: KPI definition should specify input data quality, such as sensor accuracy, sampling frequency, maximum amount of missing data points, and outlier management.
- Spatial factors: KPIs should account for the spatial distribution of sensors to ensure a representative measurement of the entire space.
- Temporal factors: KPIs should describe the time resolution for calculations, ranging from annual to sub-hourly intervals.
- Data aggregation factors: KPIs should indicate how data is aggregated in the temporal dimension, from lower-level (e.g. minute-level sensor data) to higher-level intervals for KPI calculations and, in the spatial dimension, how to aggregate sensors over large buildings with distinct thermal zones. Different aggregation methods may affect the calculations.

Spatial factors are the most influential for PMV, PPD, and PCO_2 calculations, while temporal factors and data aggregation factors play a more critical role in FF and LF computations. Importantly, the significance of these considerations depends on the specific KPIs, building characteristics, performance goals, sensor technologies, and their interplay. This again underscores the need for further research to standardize KPIs, ensuring a reliable benchmarking process for assessing building performance in practical applications.

Another assessment was done relating to the ability to source the required data for calculating relevant KPIs – with particular focus on demand flexibility. 16 flexibility related datasets were collected, covering a wide variety of building energy flexibility studies. They included data from real monitored buildings, hardware-in-the-loop setups, and numerical simulations with different building typologies. Most datasets were associated with HVAC related demand response schemes in electrical grids (e.g. testing time-of-use and other tariff/pricing programs, and testing load shifting and load shedding schemes). Only a few were connected to district heating networks.

Table 3.1 compares the variables required for calculating the different data-driven building energy flexibility KPIs and the available variables in the collected datasets. It is clear that there is a poor match between required data and available data, for most flexibility related KPIs. It is also noted that the value of a dataset (for KPI computation) does not necessarily increase with the number of variables it contains. While some datasets have many variables, they may not have the most commonly required ones for demand response assessment (Li *et al.*, 2023, Johra *et al.*, 2023a).

Table 3.1: Input variables required by the KPIs vs available ones in the collected B2G datasets (Li *et al.*, 2023, Johra *et al.*, 2023a).

Primitive variables	**% required by KPIs**	**% available in datasets**
Event timing	37.66%	18.75%
Energy consumption	35.06%	81.25%
Power demand	32.47%	6.25%
Event request action	24.68%	37.50%
Price signal	16.88%	50.00%
Energy generation	12.99%	25.00%
Event request size	11.69%	0.00%
Indoor temperature	5.19%	93.75%
Thermostat setpoint	5.19%	62.50%
Emission signal	3.90%	12.50%
Storage volume	2.60%	0.00%
Monetary incentives	2.60%	0.00%
Occupancy	1.30%	56.25%
Indoor CO2	1.30%	12.50%

Based on KPI data requirements and data availability, the three most easily calculated energy flexibility KPIs were (i) demand response energy efficiency, (ii) demand profile reshaping and (iii) energy/average power load shedding.

3.2 Data sets and data-related challenges

Collecting the right data, with sufficient data quality is challenging but essential for generating useful KPIs. More generally, data quality is an issue for all reporting and analytics services. O'Reilly (2020) surveyed 1,900 people working in the field of Artificial Intelligence, to get their perspectives on the data quality issues that they face. A wide range of data quality issues were identified (Figure 3.5).

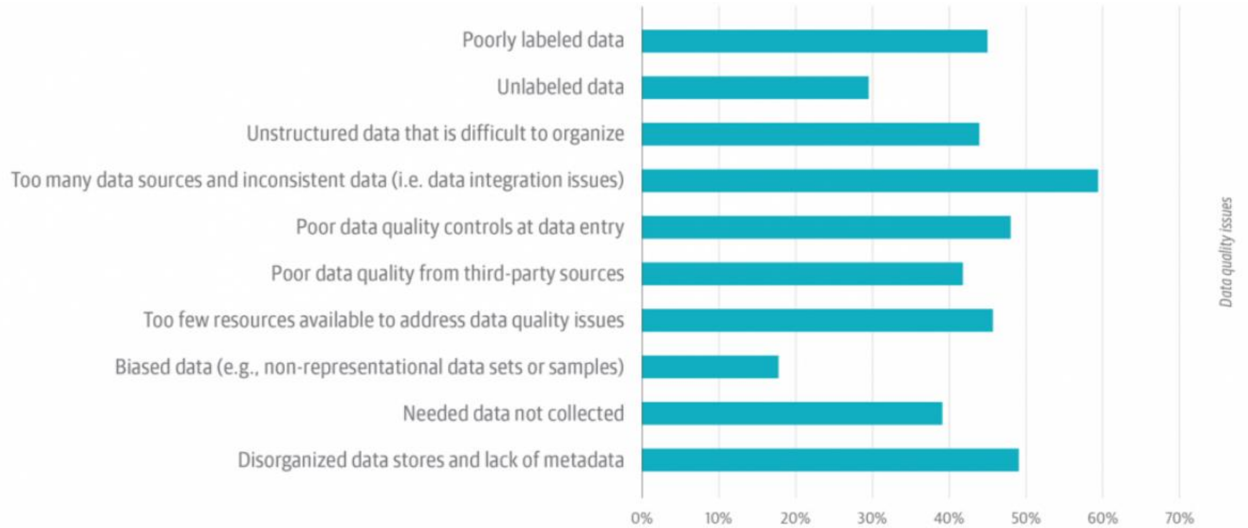

Figure 3.5: Primary data quality issues (in relation to AI) faced by respondents' organisations (Source: O'Reilly, 2020).

3.2.1 Interviews and survey results

Annex 81 participants interviewed leading practitioners to further understand industry pain points and aspirations around data quality. Sixteen industry stakeholders were interviewed representing each of Software-as-a-Service (SaaS) platform providers, design consultants, building owners, hardware suppliers and an energy retailer.

Various interview quotes, that incapsulate stakeholder sentiment on data quality and data management, are illustrated in Figure 3.6. The critical importance attributed to data quality and data management was striking. Improving data quality and data management practices was seen as one of the key actions required to foster industry growth for data-driven smart buildings.

The views expressed in these interviews form some of the logic behind the policy recommendation to "Establish Digital Ready Certification" (see Section 6.3 and Section 1.3).

A survey was also conducted to explore perspectives, across participants in the Annex, about the main challenges involved in adopting data-driven control solutions in buildings. Twenty-one (21) people responded to the survey. The survey asked respondents to rank from 1 to 7 some of the most common data challenges involved in data management in buildings. Results are illustrated in Figure 3.7 for both (i) the respondents number one major concern and (ii) a weighted score reflecting the relative importance (ranking) assigned to each issue.

"Data labelling and identification of variables" and "Data retrieval and sensor accuracy" were identified as key issues with "Inadequate or absent BAS systems" and "Non-calibrated or missing sensors" also being important. Participants were asked to provide further details about their ranking of data-related issues. The respondents consistently mentioned topics relating to data labeling, organization, retrieval, calibration, etc., as the main obstacles for the deployment of data-driven solutions.

3.2.2 Data repository

Noting the critical importance of data for researchers and for software product developers, Annex 81 participants created the 'Building Data Genome Directory' (https://buds-lab-building-data-directory-meta-directory-s0imdd.streamlit.app/ or in spreadsheet version at https://buildingdatadirectory.org/) . This directory provides links to existing publically available datasets that can be used to develop and validate energy productivity software applications. It is described by Jin *et al.* (2023b).

Its primary objective is to facilitate data-driven research to improve urban building energy efficiency, support regional energy planning, and enable effective policy formulation. By consolidating datasets, the directory significantly enhances the ability for researchers and policymakers to analyse real-world building performance and implement targeted interventions.

The datasets were consolidated from a comprehensive exploration of sources, including governments, research institutes, and online energy dashboards (Jin *et al.,* 2023a). The directory cites more than 70 datasets encompassing various data types, including building energy ontologies, energy models, energy and water usage data, electric vehicle information, weather data, building information, text-mined research data, building images, fault detection diagnostics, and occupant data. These datasets cover multiple spatial scales (meter-level, building-level, and community-level) and temporal resolutions (ranging from yearly to minute-by-minute intervals).

The aim is to provide a one-stop-shop for people to discover avaliable data-driven smart buildings datasets. The directory incorporates a crowdsourcing mechanism that allows users to suggest additional datasets for inclusion - in the hope that researchers will contribute to the directory by providing links to their datasets.

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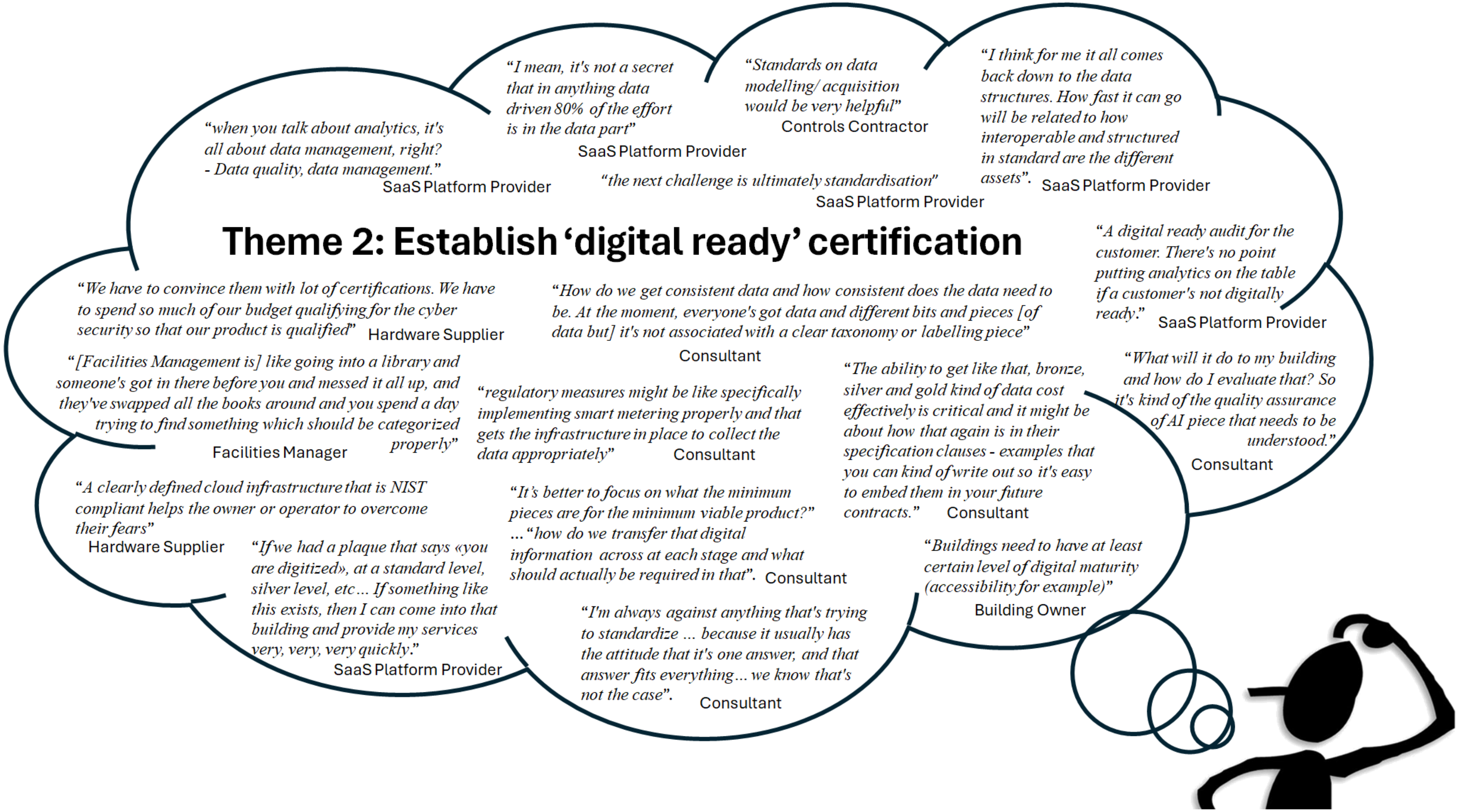

Figure 3.6: Industry stakeholder feedback reflecting on data quality and data management.

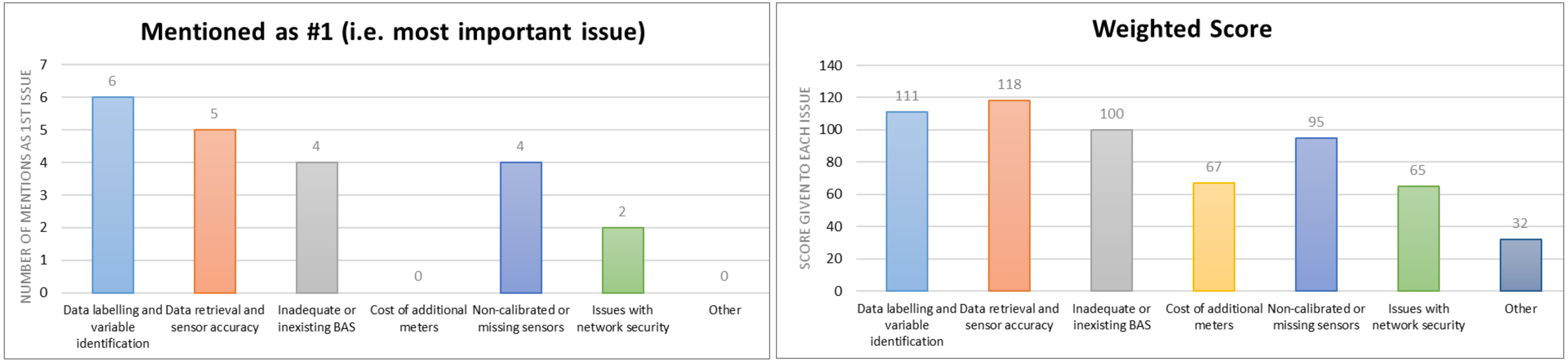

Figure 3.7: Importance ascribed to various data issues when deploying model predictive control (MPC) – Left: Frequency of being ranked as most important issue and Right: Weighted average ranking.

4. Energy Optimisation Applications

Once suitable quality data is available and accessible, it is possible to deploy energy productivity software applications (see Figure 1.2). Annex 81 research and state-of-the-art reviews (associated with some of the important energy productivity applications that can be deployed in smart buildings) are summarized in this Section.

4.1 Fault Detection and Diagnosis (FDD)

Fault Detection and Diagnosis (FDD) software is used to identify and diagnose faults (problems) in the systems and equipment operating in a building. FDD utilizes specialized algorithms to analyse data, from sensors and equipment, to identify and pinpoint the problems. This can be used by facilities managers and contractors to assist with maintenance and repair of installed equipment. It is somewhat analogous to a medical doctor using diagnostic tests to help diagnose illness in patients. In this analogy, FDD software is the building's AI doctor. Rectification-works (often by contractors) would likely be required to use the insights obtained, to fix the problems identified.

Traditional FDD will use logical if/then rules and decision trees (e.g. Figure 4.1)

	Possible Diagnoses																			
Alarm Description	Zone temperature sensor drift/failure	Airflow (DP) sensor drift/failure	Discharge temperature sensor drift/failure	Damper stuck or failed	Damper actuator stuck or failed	Reheat coil valve stuck or failed	Reheat coil valve actuator stuck or failed	AHU Supply air too warm	AHU Supply air too cool	Supply air static pressure too low	Scheduling conflict with AHU	Undersized VAV box	Tuning problem with airflow feedback control loop	Tuning problem with zone temperature feedback control loop	Inappropriate zone temperature setpoint	Minimum airflow setpoint too low	Minimum airflow setpoint too high	Maximum airflow setpoint too low	Maximum airflow setpoint too high	Sequencing logic error
High zone temperature alarm	X	X				X	X	X			X	X	X	X	X			X		X
Low zone temperature alarm	X	X				X	X		X		X	X	X	X	X		X			X
High airflow alarm		X		X	X						X		X							X
Low airflow alarm		X		X	X					X	X	X	X						X	X
Unstable airflow alarm		X		X	X					X	X	X	X			X				X
High discharge temperature alarm			X			X	X													
Low discharge temperature alarm			X			X	X													

Figure 4.1: Example of possible diagnoses for alarms associated with faults in VAV boxes (source: Smith, 2006).

In contrast, data-driven FDD is defined as software that is trained or built from data using machine learning or multivariate statistical analysis methods (Chen *et al.*, 2023). Typically, 'ground truth' data of what is considered normal and/or good operation of the building is required. The data-driven algorithms then learn what normal/good operation is, which can then be used to detect when something is deviating from this desired operation. It is noted that not all FDD software reported here is data-driven FDD.

Across numerous buildings, FDD software services have been shown to reduce energy consumption by around 9%, on average, with typical paybacks of two-years in portfolio implementations (Lin *et al.*, 2022).

4.1.1 FDD Methods

A literature review was undertaken covering the process of data-driven FDD, the systems studied, and the evaluation metrics employed. The data-driven FDD process encompasses several steps, including data collection, cleansing, preprocessing, baseline establishment, fault detection, diagnostics, and potential fault prognostics, as illustrated in Figure 4.2.

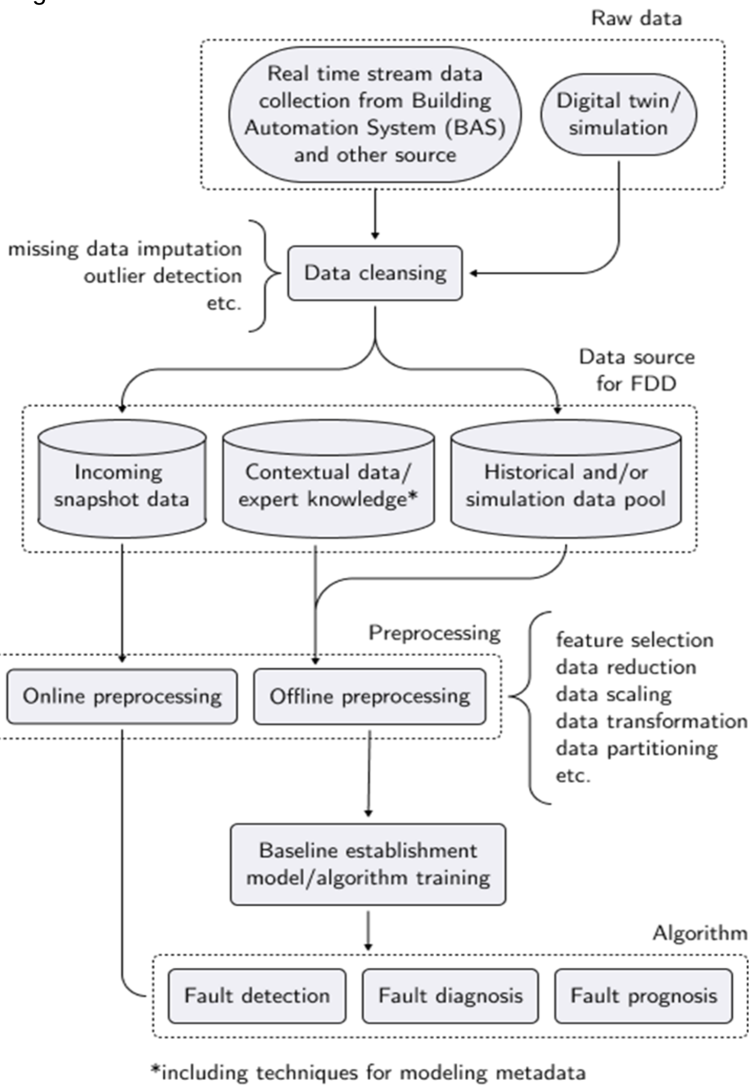

Figure 4.2: A General Data-driven FDD Process.

Several machine learning algorithms/methods can be used in the FDD process, such as Clustering, Decision Trees, Principal Component Analysis, Support Vector Machine, Support Vector Regression, Neural Networks, Bayesian Networks, Hidden Markov Models, Generative Adversarial Networks, and Ensemble Learning. These methods are reviewed by Chen *et al.* (2023). While various data-driven methods have been investigated, there are few studies that compare the performance between methods in different categories (e.g. expert rule-based vs data-driven, supervised vs unsupervised).

Our review found that data-driven FDD methods have been applied to various HVAC components and subsystems for detecting and diagnosing a range of faults. For large buildings, the focus has often been on Air Handling Unit – Variable Air Volume (AHU-VAV) systems, fan coil units (FCU), chillers, and boilers. 35% of studies were dedicated to secondary AHU-VAV systems, with chillers following closely at 32%. Studies on AHU-VAV secondary systems (crucial for heating and cooling across multiple zones), were often presented with actuator and equipment faults such as those in dampers, cooling/heating coil valves, fans, and air ducts.

Chiller faults were extensively studied, in the context of data-driven methods in Vapor Compression Cycle systems. Two categories were identified for chiller faults: (1) Local faults which include faults like condenser fouling, reduced condenser water flow, non-condensable in the refrigerant, and reduced evaporator water flow, and (2) System faults such as refrigerant leakage/ undercharge, refrigerant overcharge, and excess oil.

Significant focus (accounting for 17% of the reviewed studies), has been directed towards whole-building level faults. The intricacies at this level arise from a confluence of factors such as building dynamics, external climatic conditions, system operating schedules and occupant comfort requirements. These collectively give rise to a myriad of building energy consumption patterns, which are not always straightforward to discern.

Regarding the sources of data used in developing these FDD methods, the literature revealed a mix of simulation data, laboratory experiments, and field measurements from real buildings. Among the papers reviewed, 48% used lab experiment data, 20% used simulation data, and 32% used real building data. The majority of studies relating to whole building applications relied on real field measurement data, while system-level VRF, AHU and Chiller applications mainly relied on laboratory data.

Evaluating the efficacy of data-driven FDD is crucial. The literature presents a gamut of dedicated metrics to achieve this. Broadly, these metrics fall into three categories:

- General Evaluation Metrics: These encompass fundamental measures like true positive rate (TPR), false negative rate (FNR), and correct diagnosis rate (CDR).
- Classification Problem Metrics: Tailored for data-driven classification problems, these include confusion matrix, F-measure (or F-score), Receiver Operator Characteristic, and Area Under the Curve metrics.
- Statistical Significance Tests: Useful for comparing different classification models in FDD, common tests include the t-test, McNemar's Test, and the Friedman Test.

Based on findings from the review, some of the identified ongoing focus areas and challenges – required to further the development and market adoption of data-driven FDD – include:

- Real-building deployment
- Performance Evaluation, Benchmarking, and Fault Impact Analysis
- Scalability and Transferability
- Interpretability
- Cyber Security and Data Privacy
- User Experience

Further details on these challenges and the literature review are presented in Chen *et al.* (2023).

Based on the summarized literature, data repository, and existing FDD software tools, participants of this activity developed a roadmap (see Section 6.2), aiming to guide industry stakeholders through the ecosystem of Fault Detection and Diagnosis.

4.1.2 Test Cases and Software Review

A persistent challenge to ongoing development of FDD is a lack of common datasets and algorithm test methods. These are essential to support the vetting of new algorithms. Unfortunately, available public datasets are generally limited to a few types of HVAC equipment, and the fault types and the range of faulty data are small. For example, the ASHRAE RP-1043 project included 8 fault types for chillers (Braun J., 2006). The ASHRAE RP-1312 project included 13 faults for air handling units (Wen and Li, 2012). For both datasets, each fault type contains faulty data ranging from one day to a few days within one typical operational season.

To bridge this gap, researchers at Lawrence Berkeley National Laboratory developed a large and diverse database of FDD datasets. It includes data from 7 HVAC systems, including (i) a single duct AHU system, (ii) a packaged rooftop unit (RTU), (iii) a dual duct AHU system, (iv) a fan coil unit (FCU) system, (v) a fan power unit (FPU), (vi) a boiler plant, and (vii) a chiller plant. Data for most systems spans faulty operation across a full year. The total fault cases number 257 (i.e., faults at different severity levels), with an associated 8 billion data points. The FDD datasets and associated inventories are publicly available at https://faultdetection.lbl.gov/. The FDD data set is documented at Granderson *et al.* (2020) and Granderson *et al.* (2023). Frank *et al.* (2019) presents a systematic framework for evaluating the performance of FDD algorithms.

The ecosystem of commercially available FDD software tools was also reviewed. A diverse range of FDD software products was identified, including (i) products that are hosted in cloud-based and/or on-premise servers (external to the BMS), and (ii) products that can be run from desktop applications, or embedded in equipment (Granderson *et al.*, 2018). Building management systems (BMS) often offer collections of rules that are packaged and sold as FDD libraries. Some examples of available software and corresponding vendor information is provided by Wen *et al.* (2025).

4.2 Model Predictive Control (MPC)

Model-based Predictive Control (MPC) is a promising application for improving the performance and operation of building HVAC systems. In this control approach, a suitable mathematical model (digital twin) of the building and its systems, provides forecasts of how the building will behave over the forecast future time horizon. This allows a supervisory controller to schedule equipment in advance, to optimise for comfort and energy savings. For example, if the forecast is for warm weather over the day, then a supervisory controller can prevent heating equipment from turning on first thing in the morning. The general process is illustrated in the Figure 4.3 schematic.

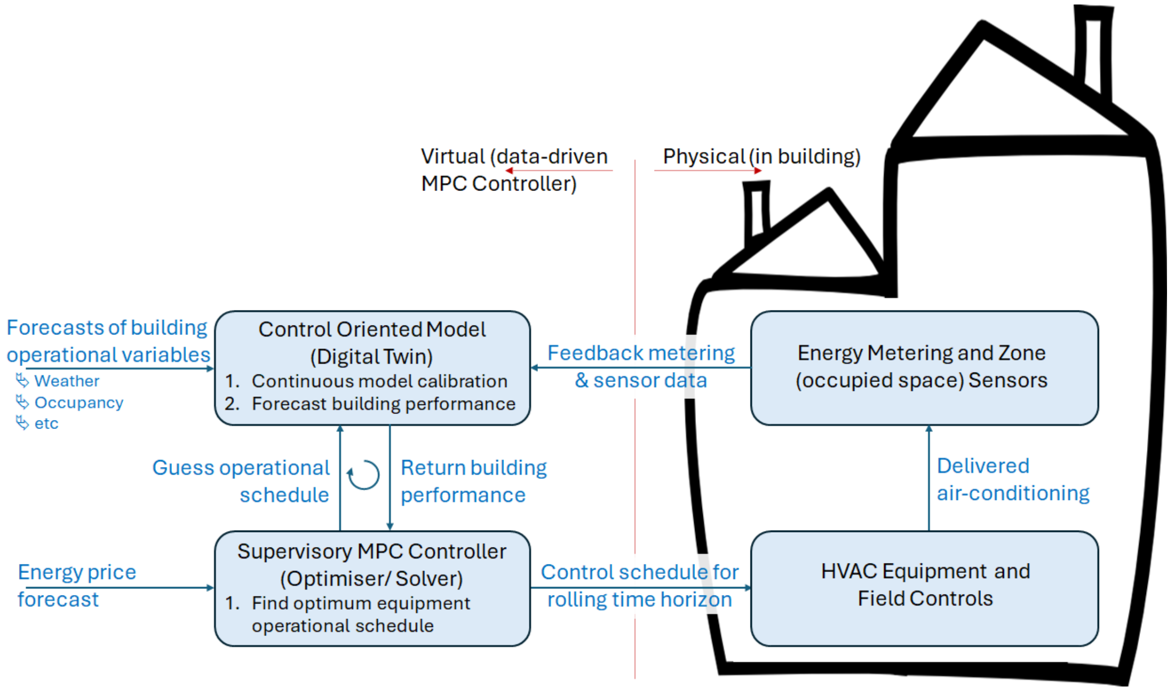

Figure 4.3: Schematic representation of model-based predictive control.

MPC is useful in virtually any situation where knowledge of the future, within a reasonable timeframe, allows for better decision-making. For example, a solar radiation forecast enables the planning of electricity use based on the anticipated electrical production of solar panels. Foreknowledge of occuapancy can also be used to manage when and where to provide HVAC services. MPC can also be used to optimise energy storage in Building-to-Grid applications (see Section 4.3)

As illustrated in Figure 4.3, the key components of the Model Predictive Controller are:

- **Control-oriented model**. This is a simplified mathematical model of the building used to forecast the future state and the energy consumption of the building - if different control actions were to be taken. The control-oriented model is called up by the MPC controller/optimiser in an iterative fashion to explore alternative supervisory control actions until it finds an optimal solution for the given objective. Noting that the control oriented model is an approximate model, it will typically be continuously recalibrated by comparing its forecasts with actual outcomes measured in the building.

- **MPC controller**: ("optimiser" and "solver" are synonimous words used in the text below). This is the assembly of control algorithms that interogate the control-oriented model to determine the best course of action – taking into account forecast externalities. It optimises according to an objective function or reward signal. This cost/reward function can include KPIs relating to total energy cost, energy use, electric peak demand, GHG emissions, thermal comfort limits, wear and tear of equipment, etc.
- **HVAC controller**: This is the physical control equipment in the building. It activates the instantaneous response of the HVAC equipment to achieve control-setpoint conditions in the building (for example using appropriate "PID" loops (proportional, integral, derivative control)). In itself, the HVAC controller has no visibility of the future, and can not optimise in the light of forecasts or higher level building awareness. The MPC controller passes a time series schedule of new values for the setpoints to the HVAC controller, to achieve the optimisation (rather than have the HVAC controller controlling to a single fixed setpoint).
- **Metering and sensors (data collection)**: A feedback loop is provided by sending meter data and sensor data from the building to the control-oriented model. This allows the simplified control-oriented model to be regularly recalibrated so that it does not drift too far from reality. Diverse data streams may be used, including weather conditions (ambient temperature, solar irradiance, humidity, etc.), sensor data from the occupied space (temperature and other IEQ data, occupancy etc), and equipment operational data (taken from the building's BMS and/or IoT sensors).

Serale et al (2018) conducted a review of the various implementations of MPC reported in the literature. They focussed on the potential to enhance building and HVAC system energy efficiency. They found that MPC implementations gave energy savings ranging from 0% to 40% (Figure 4.4).

A related alternative data-driven supervisory control approach is based on Reinforcement Learning (RL). The RL approach has the potential to avoid the need for a control-oriented model and the need for supervised learning of building performance. It does this by using a more trial and error based approach that explores the state-space, to find the control action (policy function) that maximises the given reward function. The difficulty for RL approaches is in obtaining sufficient data to explore the state-space and derive an appropriate control policy.

Annex 81 research on data-driven control focused on reviewing and benchmarking the performance of MPC and RL controllers using common data libraries and test environments.

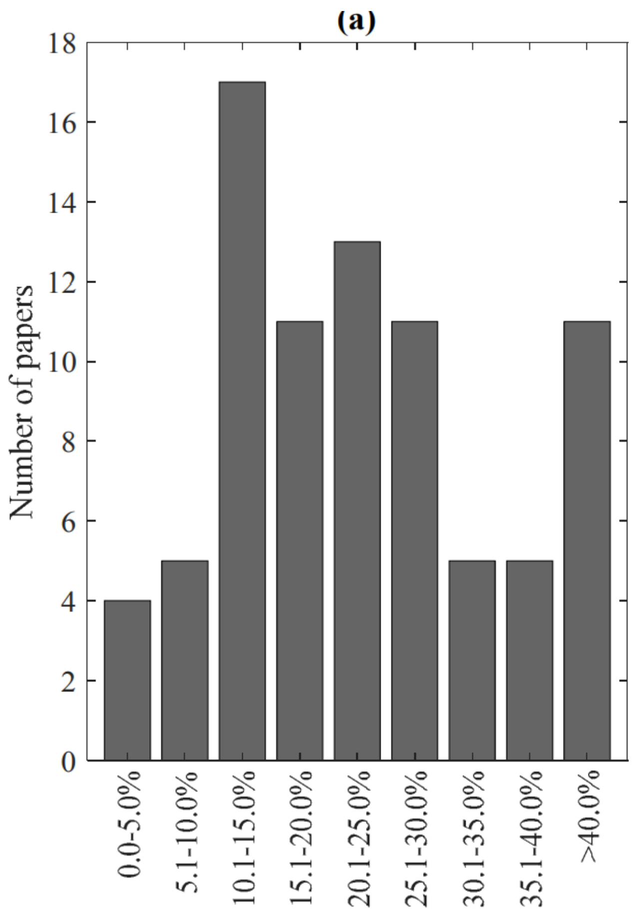

Figure 4.4: Number of papers claiming various levels of energy savings, when implementing model predictive control (MPC) in buildings Serale et al (2018).

4.2.1 Test Cases and Algorithm Benchmarking

Data from Test Cases

Annex 81 participants collaborated to compile a diverse range of datasets that could be used for developing and testing advanced control applications. Initially, more than twenty test cases were collected for consideration from all the participants in the Annex who provided the necessary information through a common template. These cases corresponded to real buildings, from experimental/lab setups and from simulated buildings. Six of these were chosen as exemplar test cases from real buildings, where both the available dataset itself and the metadata (i.e. relevant contextual information) were of high quality.

The datasets have been made public, and are available for download at the Mendeley Data repository at https://data.mendeley.com/datasets/xztfbtsgys/3. The datasets are described in detail in an open access data paper (Sartori *et al.*, 2023). Some features of the collected datasets are provided in Table 4.1. Readers are encouraged to go to the references if they would like to access these datasets.

Table 4.1: Annex 81 exemplar MPC datasets.

Location	Building Typology	HVAC and other equipment
Oslo, Norway	3,800m^2, eight story office building	District heating.
Trondheim, Norway	‘ZEB Living Lab’ detached house	Either floor heating, a central radiator, or air ventilation
Lyngby, Denmark	‘FlexHouse’ detached house	Hydronic heating
Varennes, Canada	2,100m^2, two story library	110.5 kW BIPV solar with heat recovery, geothermal heat pump with hydronic heating
Berkeley, USA	‘FLEXLAB’ testbed representative of 57m^2 commercial office	Single-zone variable-capacity AHU with chiller and boiler. 3.6kW Solar PV and 7.2kWh battery
Singapore	46m^2 testbed office	Variable air volume AHU

BOPTEST Benchmarking Test Environment

Annex 81 participants also contributed numerous studies, demonstrating the value and advantages of various control approaches in different buildings and use-cases. While valuable in their own right (for identifying promising approaches), these individualized case studies are difficult to compare and contrast. This makes it difficult to generalise findings about the advantages and disadvantages of different approaches when used in different scenarios.

So, in addition to providing data for researchers, the Annex conducted benchmarking studies to compare the efficacy of various data-driven controllers in a controlled test environment. The Building Optimisation Testing (BOPTEST) framework (Blum *et al.*, 2021), was used for this purpose. More detail on BOPTEST can be found at the homepage at https://boptest.net.

Rather than use real buildings for testing, the BOPTEST framework uses simulated virtual buildings. This enables software developers and researchers to test their algorithms without interrupting the operation of a real building. And it provides a consistent test environment for everyone.

The virtual buildings (for benchmarking purposes) are called **emulators**. These are high-fidelity simulation models of specific building systems which are used to replicate, as closely as possible, the behaviour of a real system at appropriate time scales for building operation. It enables testing and evaluation of advanced control strategies in a closed loop (i.e., “offline”, within a confined computer simulation). This is the next best thing to a real building. These emulators are more sophisticated/detailed models than the control-oriented models described previously.

A visualization of the BOPTEST test environment is shown in Figure 4.5.

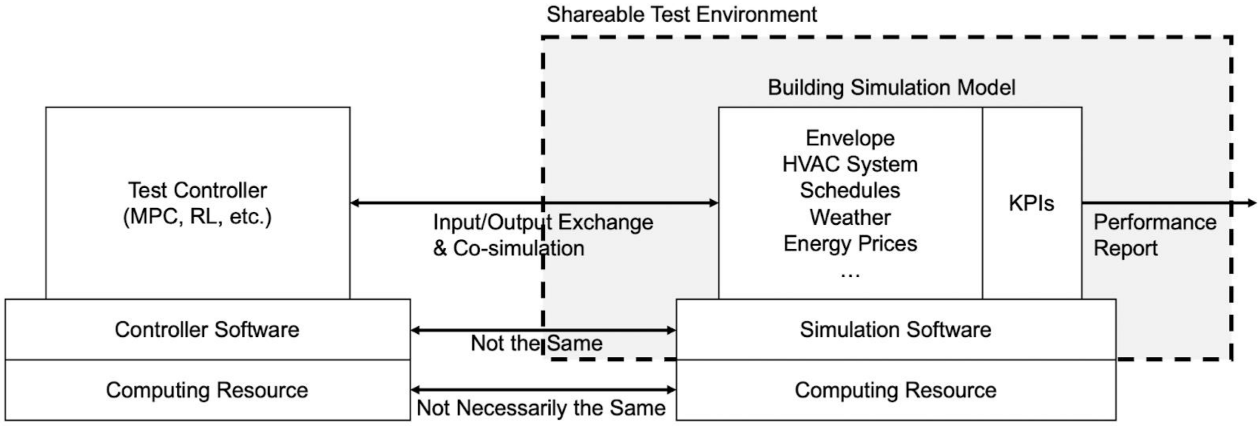

Figure 4.5: Elements of a test environment for benchmarking control performance.

The BOPTEST test environment encapsulates the building emulator with any boundary condition data and parameters needed to run the model. It also contains the simulation software and solvers needed to integrate the simulation model through time. The test environment also calculates relevant KPIs, independent from the MPC software developer, to unambiguously enable comparison between different products/ solutions. The BOPTEST environment has an API which the user can use to manage tests and input/output data between the controller (that is being benchmarked) and building simulation model.

BOPTEST currently offers a selection of eight publicly available test case emulators: (i) BESTEST Air, (ii) BESTEST Hydronic, (iii) BESTEST Hydronic Heat Pump, (iv) Single Zone Commercial Hydronic, (v) Two Zone Apartment Hydronic, (vi) Multizone Residential Hydronic, (vii) Multizone Office Simple Air, and (viii) Multizone Office Simple Hydronic. These test cases are written in Modelica and use open-source Modelica libraries extending from the Modelica IBPSA Library (https://github.com/ibpsa/modelica-ibpsa). Test cases may also use Spawn (Wetter *et al.*, 2024) to integrate envelope models written for EnergyPlus with HVAC and control models written in Modelica. Each test case contains an embedded baseline controller, so that test controllers can overwrite any subset of control signals at the supervisor or actuator levels.

4.2.2 Control-Oriented Modelling Techniques

Key to the efficacy of model predictive control (MPC) is the forecasting performance of the control-oriented model, that is embedded with the MPC controller.

Modelling approaches are traditionally classified using the categories of "white-box," "grey-box," and "black-box" models (Figure 4.6).

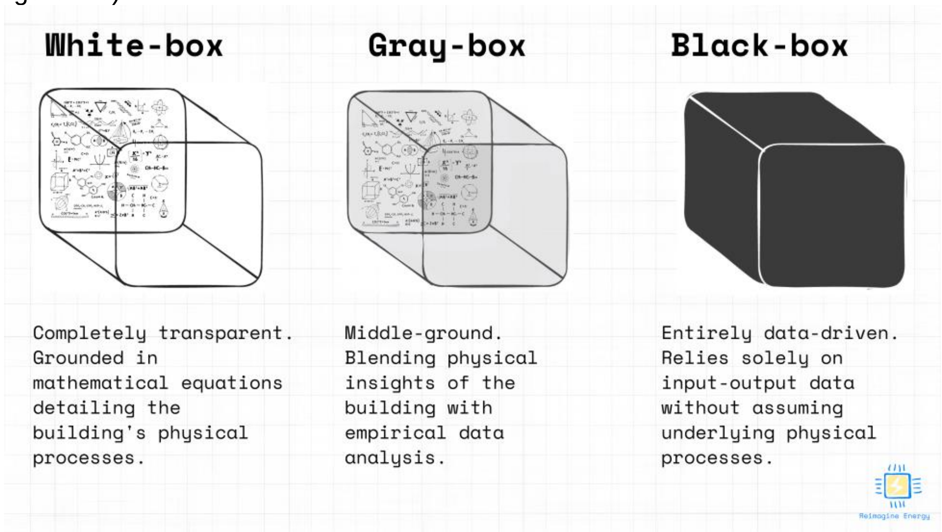

Figure 4.6: White-box, gray-box and black-box models (image credit: Benedetto Grillone, https://benedettogrillone.substack.com).

White Box Models

A white-box model is based on parameters with clear physical meanings. The equations rely on an aggregation of well-understood physical phenomena, such as energy balance equations at specific locations, heat transfer coefficient correlations, and radiative heat transfer models. Both the equations and their associated parameters are clearly and explicitly derived. They are often created using building performance simulation tools such as EnergyPlus, TRNSYS, and Modelica. White-box models have several advantages: interpretability and extrapolation under unusual or unforeseen situations. White-box models can also be calibrated with real measurements: temperatures, flow rates, electric power measurements, etc.

Emulators in the BOPTEST framework are white box models, as they are arguably the closest match to an actual building. However, their set up complexity and the long computational time required to run them, will typically prevent them from being a control-oriented model.

Black Box Models

In contrast with white-box models, black-box models describe mathematical relationships between a set of inputs and outputs. They are purely data-driven, and their parameters do not have an explicit physical meaning. There are a wide variety of black-box modelling approaches, including:

- Linear and non-linear regression: The oldest black-box modelling approach, the least squares method involves finding the coefficients of a function (which can be either a linear or non-linear function of the inputs) that will minimise the difference (typically measured using the mean square error as a parameter) between predicted values and measured output variables.
- Time series methods: Time-series models are a mathematical framework in which the output variable depends on past values of the output variable collected at regular intervals (autoregressive model) and on present and past values of input variables (exogenous variables).
- Machine learning methods: including (i) decision trees, (Yu *et al.,* 2010), (ii) neural network models (Afram *et al.,* 2017; Macarulla *et al.,* 2017), (iii) support vector machines (Dong *et al.,* 2005), (iv) Gaussian process regressions (Maddalena *et al.,* 2022), (v) gradient boosting models (Miller *et al.,* 2020), etc.
- Deep learning methods (LeCun *et al.,* 2015): including (i) recurrent neural networks (Fan *et al.,* 2019), and (ii) long short-term memory (LSTM) networks (Mtibaa *et al.,* 2020).

Black-box models can be rapidly deployed, require less knowledge about the building systems, and they can achieve a high degree of accuracy. However, black-box models also have shortcomings. They require a significant amount of high-quality data for their creation, some expertise and skill is required in selecting appropriate input variables, and they lack extrapolation capability.

Grey Box Models

A grey-box model represents a compromise between a white-box and a black-box model. While it does not include as many details as a white-box model, its parameters still retain physical meaning, typically as "effective" or “equivalent” values. However, unlike white-box models (where parameters are derived from physical properties or the building’s geometry), a grey-box model's parameters are calibrated from collected data, akin to a black-box model.

The classic grey-box model (albeit not the only one) is a thermal resistive-capacitive (RC) network. Figure 4.7 shows an example of an RC network for a small building. The nodes 1, 2 and 3 represent respectively the temperatures of the indoor air, the inner walls and floors and the building envelope. The thermal capacitances represent the effective energy storage capacity of these components, and the resistances represent the effective thermal resistance between them, including the resistance between specific nodes and the outdoor air. For instance, R_{1ext} represents the equivalent thermal resistance between the indoor air and the ambient air (this kind of direct link can be the result of infiltration and heat loss through the fenestration). Q_{SG}, Q_{IG} and $Q_{heating}$ respectively represent the thermal contributions of solar gains, internal gains and the heating system.

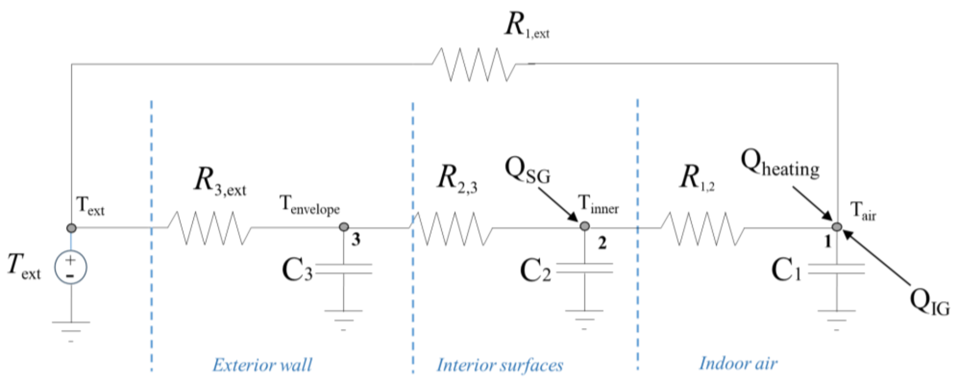

Figure 4.7: Example of grey-box model: RC representation of a simple building.

In this case, the RC network in Figure 4.7 is a "third order" network, as each capacitance defines a differential equation. The actual value of these parameters (e.g., the resistances in K/W or the capacitances in MJ/K) may be calibrated by collecting data from a real system.

There is an element of subjectivity in defining an RC network, where other parameters could have been included (increasing or decreasing the "order" of the network). However, it is important to remember that the primary objective of this type of model is only to offer a simplified representation that enables the MPC controller to make short time-horizon decisions.

Characterising uncertainty stemming from sensors, model approximations, and unrecognized disturbances is important for implementing sensor-driven and real-time controllers. Grey-box models provide a useful framework for handling such uncertainties, as they can be formulated as SDEs (stochastic differential equations, i.e., differential equations that incorporate randomness). These SDEs can contain (i) a diffusion term (to account for modelling approximations, account for un-modelled inputs and noise in measurement of input variables), and (ii) a noise term (to account for noise in measurements of output variables). The use of SDEs is an evolving area of research.

4.2.3 Data-Driven Control Benchmarking Studies

Five benchmarking studies were performed by Annex participants. The scenarios investigated are detailed in Table 4.2.

Table 4.2: Annex 81 Benchmarking Studies

Study	Study Objective	BOPTEST Test Case	Control Optimization	Control Oriented Model (for MPC)
1	Evaluate the performance and scalability of an MPC framework across different buildings	1. BESTEST Hydronic Heat Pump 2. Single Zone Commercial Hydronic	Economic optimisation of space heating, via room temperature setpoint, for three price scenarios (constant, dynamic, and highly dynamic)	Three-state linear RC model (grey-box)
2	Compare the performance of Deep Reinforcement Learning (RL) and Model Predictive Control (MPC) approaches	BESTEST Hydronic Heat Pump	Economic optimisation via compressor speed control for • Typical heat day • Peak heat day Using the BOPTEST highly dynamic pricing scenario	Reduced-order (1R1C) model with regression-based heat pump model (grey-box)
3	Compare the performance of alternative black box control-oriented models for MPC	Multizone Office Simple Air	Energy optimisation over a week in summer and a week in winter	Various black-box (Linear, Multilayer Perceptron, LSTM)

4	Demonstrate the benefits of a tube-based MPC controller for managing model prediction uncertainties	BESTEST Air	Economic optimisation of space heating and cooling for 1. Peak heat day 2. Typical heat day 3. Peak cool day, and 4. Typical cool day.	first-order thermal RC model (1R1C)
	Investigate the benefits of incorporating predictive information into Soft Actor Critic (SAC) Reinforcement Learning (RL) controller			Not applicable
5	Compare Deep Reinforcement Learning (RL) and Model Predictive Control (MPC) against true optimal control	Not applicable (used bespoke test environment)	Optimisation to a weighted reward function including energy costs, thermal comfort, and control slew rate	Perfect forecast

All studies found that the MPC and RL controllers substantially out-performed the BOPTEST's rule-based control strategies, in terms of providing better thermal comfort for occupants (lower Kelvin Hours (Kh) outside of the target comfort thresholds) and reducing energy costs by around 20%.

Based on the studies performed, it is possible to directly compare performance results for the MPC and RL controllers used in Studies 1 and 2, and from a previous study (Arroyo *et al.*, 2022). This is because all of these studies used the BESTEST Hydronic Heat Pump test case from BOPTEST with (i) the *peak_heat_day* and *typical_heat_day* time period scenarios and (ii) the *highly_dynamic* electricity price scenario. The comparisons are illustrated in Table 4.3 and Figure 4.8. The best MPC solutions typically outperformed the best RL solutions.

Table 4.3: Comparison of data-driven approaches for the bestest_heat_pump_hydronic test case in BOPTEST.

bestest_heat_pump_hydronic		Peak Heat Day Period		Typical Heat Day Period	
Highly Dynamic Electricity Price		Operational Costs (EUR/m2)	Thermal Discomfort (Kh/zone)	Operational Costs (EUR/m2)	Thermal Discomfort (Kh/zone)
Baseline		0.91	8.38	0.41	9.44
Benchmark (Arroyo et al, 2022)	RL (DDQN)	0.82	2.80	0.51	180.84
	MPC 15 min Step	0.66	1.15	0.28	7.24
	MPC 60 min Step	0.76	2.67	0.30	7.06
Study 1 (Walnum et al, 2020)	MPC 15 min Step	0.80	0.02	0.37	6.39
	MPC 60 min Step	0.82	1.15	0.34	7.99
Study 2 (Wang et al, 2023)	RL (DDPG)	0.81	0.87	0.35	7.73
	MPC 60 min Step	0.71	0.00	0.31	8.29

These results are from a relatively small number of studies. Further benchmarking research is required to build up the evidence base to cover more buildings and different approaches and to investigate design choices for data-driven control. Collaboration on common test cases is essential to ensure such studies are comparable. Future work should also benchmark solutions on more complex HVAC system designs and more building types than performed in this study, as well as in real buildings. Continued work on BOPTEST and activities within IBPSA Project 2 are aiming to address such needs.

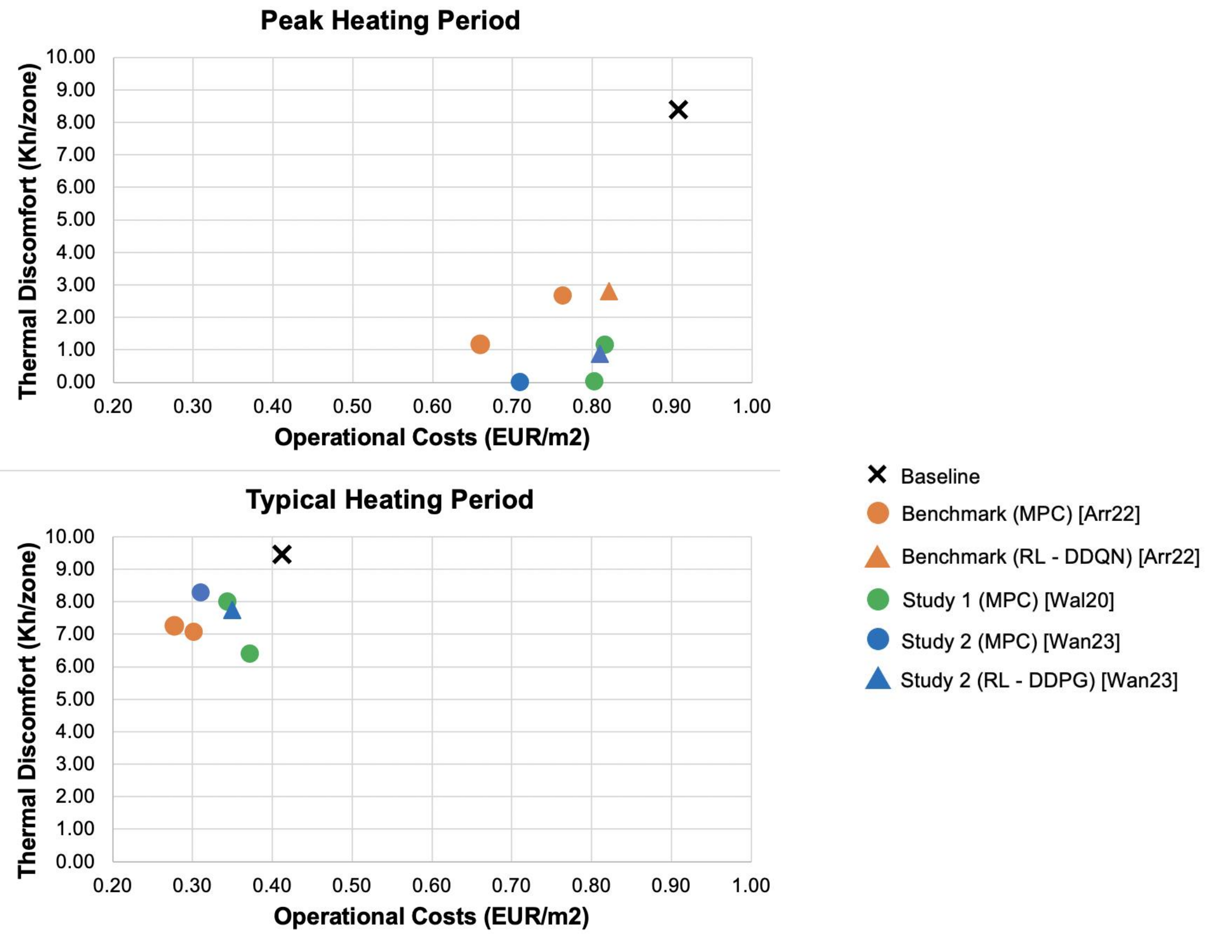

Figure 4.8: Performance of different data-driven control strategies in the BOPTEST Peak Heating Day (top) and Typical Heating Day (bottom), using the 'Highly Dynamic' electricity price scenario, in the BESTEST Hydronic Heat Pump test case. (Baseline is BOPTEST's built in rules based controller).

4.3 Buildings to Grid

In addition to improving energy efficiency (reducing overall consumption), the IEA identifies the need to 'enhance system-wide efficiency' (IEA, 2022). This includes the emerging need for load shifting (i.e. managing the time of energy consumption) (IEA, 2023a). Load shifting in buildings can be achieved with various thermal and electrical energy storage assets that routinely occur in buildings (e.g. hot water, HVAC, electrical batteries, electric vehicles). These assets are known as 'flexible' loads and are capable of being dispatched using modern digital technologies.

Building energy flexibility strategies (in the form of demand response) enable load control/modulation to provide building-to-grid (B2G) services to local energy grids. These services are expected to become a critical resource for improving the security of energy systems, as part of the transition to variable renewable energy resources. In their Net Zero Emissions by 2050 Scenario, the IEA is calling for a tenfold increase in demand response availability from buildings between 2020 and 2030 (IEA, 2023b).

Supporting these high-level ambitions, Annex 81 research focussed on (i) identifying definitions and KPIs for building energy flexibility assessment, and (ii) the task of utilising data-driven methods for calculating these KPIs. These KPIs should take into account the heterogeneity of data representations in datasets relating to B2G services. This Annex 81 research promoted the use of ontologies and semantic principles to standardie the definitions and computation of KPIs.

4.3.1 Measuring Demand Flexibility Outcomes

A literature review was conducted on ways to quantify the demand flexibility available from both single buildings and from clusters of buildings. Of the studies reviewed, 49% focused on residential buildings and 28% focused on commercial buildings. 53% of studies considered flexibility at single-building level and 41% considered flexibility at building cluster level. Only 26% of the studies involved real measurements of flexibility, with 65% relying on numerical simulations (Li *et al.*, 2023).

The review highlighted two main constraints in quantifying energy flexibility through operational building data analysis, being (i) the lack of robust data-driven approaches for generating baseline load profiles when demand response is not activated (which are necessary for calculating baseline-dependent KPIs) and (ii) the lack of KPIs that can be computed without need of baseline or reference scenario inputs (i.e., baseline-free KPIs).

A total of 81 distinct data-driven KPIs were identified in the reviewed scientific literature on building demand response. Table 4.4 and Table 4.5 show the most popular (most frequently used in scientific studies) data-driven energy flexibility KPIs.

Table 4.4: Most popular KPIs that require a baseline for assessing demand response and energy flexibility (Li *et al.*, 2023, Johra *et al.*, 2023a).

KPI denomination	Definition
Energy efficiency of demand response action	The difference in total energy use between the scenario with demand response and the reference scenario without demand response over a complete cycle, divided by that over the period of the demand response action
Flexibility savings index	The ratio between the energy costs of the scenario with demand response and the energy costs of the reference scenario without demand response
Peak power shedding	The difference between the peak power use of reference scenario without demand response and the peak power use of the scenario with demand response

Table 4.5: Most popular baseline-free KPIs for assessing demand response and energy flexibility (Li *et al.*, 2023, Johra *et al.*, 2023a).

KPI denomination	Definition
Flexibility factor	The difference between the energy use during non-peak periods and peak periods divided by the sum of energy use during non-peak periods and peak periods
Energy shift flexibility factor	The difference between the energy use during low-price periods and high-price periods divided by the sum of energy use during low-price periods and high-price periods
Load factor	The ratio between the average power use and the maximum power use

As discussed in Section 3.1, 81% of the data-driven energy flexibility KPIs found in the scientific literature require a baseline to be computed. Establishing such a baseline energy profile (a counterfactual energy demand if no demand response event had occured) is challenging. Ideally, the baseline calculation method would be robust, transparent and impervious to possible gaming of B2G service markets. Currently, there is no consensus about which data-driven energy demand baseline generation method would perform best, especially at low aggregation levels (Li *et al.*, 2023, Johra *et al.*, 2023a).

The most common data-driven methods for baseline generation in single-buildings and in district energy applications are as follows:

- **Control group methods**: Construct a baseline from monitoring data of buildings that are similar to the target ones with equivalent boundary conditions (weather, occupancy, operation) but do not perform any demand response at the time of evaluation (Li *et al.*, 2023).

- **Averaging methods** (similar day look-up approach or *XofY*): One of the most popular *XofY* load estimation technique is the *HighXofY*, which takes the average load of the *X* highest demand days from a set of *Y* admissible days prior to the demand response event (Li *et al.*, 2023).
- **Regression models**: Load forecasting is often performed with robust autoregressive models, such as ARMA (Auto Regressive Moving Average), ARIMA (Auto-Regressive Integrated Moving Average), GAM (Generalized Additive Model), or LASSO (Least Absolute Shrinkage and Selection Operator). However, these models may require large amounts of historical data to get a good fit (Li *et al.*, 2023).
- **Shallow machine learning methods**: Currently, many popular machine learning methods employ relatively simple models with a small number of layers or processing stages (shallow artificial neural networks, decision trees, random forests). These models present a limited capacity to learn complex and non-linear patterns from multi data with high dimensionality. They are thus only adequate for data with relatively simple patterns and straightforward relationships between features and outputs.
- **Deep machine learning methods**: In recent years, deep machine learning methods have emerged to leverage deep neural networks (DNN) with a very large number of hidden layers and neurons, recurrent architecture and attention mechanisms. These DNNs are very well suited to learn intricate patterns and representations from time series data (typical dynamic data from building systems) and generate forecasts of building energy profile and indoor environment variations (sequence-to-sequence forecasting) (Chaudhary *et al.*, 2023a; Chaudhary *et al.*, 2023b). In particular, long short-term memory and time-delay neural networks, have gained popularity for building energy profile forecasting. However, DNNs require a large amount of training data to outperform more simple and robust statistical methods. Large building operation datasets with sufficient quality for DNN training are scarce, but this limitation can be mitigated by employing transfer learning principles and synthetic data generators (Chaudhary, 2023c).
- **Hybrid models**: Combining some of the abovementioned modeling approaches has also been explored as a means of performing load demand forecasting.

4.3.2 Datasets and Test Cases

Annex81 research sought to gather datasets (in the form of time-series meter and sensor data, along with appropriate metadata and case descriptions) of demand response activities, in the hope that they could be used to further develop, study, test and benchmark B2G services.

330 datasets were identified as potentially of interest. Of these, only 16 were deemed adequate with proper descriptions and open access (or soon to be open access) data (see Figure 4.9). A large share of the dataset candidates were miscategorized, out of scope, without sufficient description or unavailable to participants outside of the original research group that had generated the data (Li *et al.*, 2023).

Datasets are available through an online platform (web-app) for the collection and analysis of building demand response datasets. It can be accessed at the following link: https://aau-ef-kpi-web-app.build.aau.dk/ (see also Johra *et al.* (2023))

4.3.3 Toolbox for Data-Driven Assessment of Energy Flexibility

Annex 81 participants developed an open-source Python toolbox, to help different building stakeholders (building owners, tenants, building managers, policymakers, utility companies, and grid operators) to assess demand response and energy flexibility from buildings. This Python package leverages the EFOnt ontology (Li and Hong, 2022) to apply semantic principles for the standardization of KPI definitions and computation. A semantic/ontology-based approach appears to be the best way to streamline demand response assessment from commonly available operational building data. It ensures the interoperability of the toolbox with the different elements in the B2G ecosystem, and supports the portability of the B2G services across heterogeneous buildings.

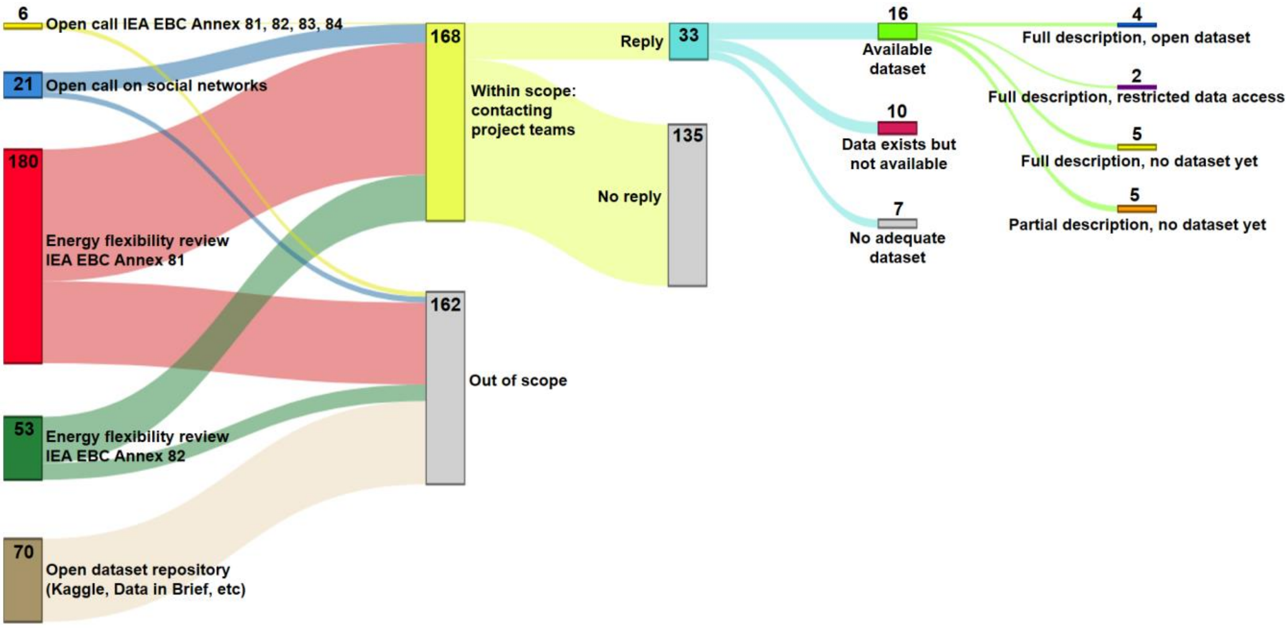

Figure 4.9: Building demand response dataset collection campaign by Annex 81 (Li *et al*., 2023).

Combined with other relevant ontologies, representing various useful knowledge domains for B2G services, the EFOnt ontology enables the creation of semantic data models that can facilitate standardisation of the demand response KPIs' definition, their data specification/requirements, data collection procedure, pre-processing, computation procedure and visualisations (see Figure 4.10). The demand response and building energy flexibility KPIs found in the scientific literature are progressively implemented in the *energy-flexibility-kpis* Python package, together with all necessary data treatment sub-functions and key data-driven methods for generating an energy profile baseline (Johra *et al.*, 2023a, Li and Hong, 2022).

This *energy-flexibility-kpis* Python package for the assessment of demand response and energy flexibility strategies can be found in the dedicated GitHub repository https://github.com/HichamJohra/energy_flexibility_kpis (under development) and can be installed from pypi.org (https://pypi.org/project/energy-flexibility-kpis/): *pip install energy-flexibility-kpis*.

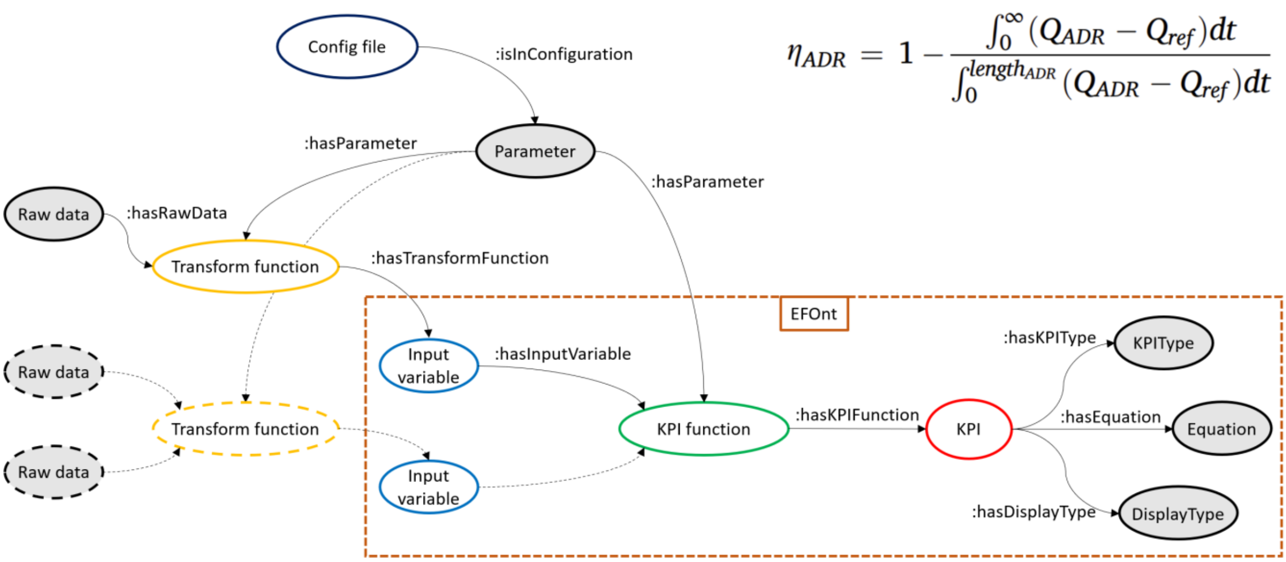

Figure 4.10: Semantic description of an energy flexibility KPI and its input variables in the EFOnt ontology (Johra *et al.*, 2023a, Li and Hong, 2022).

5. Case Studies

A focus of Annex 81 research was to collect case studies of data-driven smart buildings. Based on surveyed stakeholder preferences, the aim of this work was to (1) gather evidence from real-world implementations, (2) capture stakeholder perspectives and context, (3) identify and summarise business models, (4) highlight relevant applications and use-cases, and (5) document specific technologies and technology stacks.

Collectively, these case studies establish an accessible evidence base that outlines common challenges and critical insights, thereby facilitating the wider adoption of data-driven smart buildings. Emphasis was placed on clearly communicating the benefits, lessons learnt, and challenges encountered, and ensuring the content was accessible both in terms of availability and level of detail to a broad audience.

The resulting collection of case studies is accessible at https://datasmartbuildings.org/ and an open-access book is in preparation.

5.1 Methodology for case study collection

A standardised two-page template was developed to enable case study information to be gathered consistently. An initial draft template was systematically refined through several co-creation workshops involving diverse stakeholder groups, ensuring the captured data was relevant to various fields. The final template specifically aimed to collect (a) general details such as the case study's location, installed technology, data availability, and implementation status (Figure 5.1: top); (b) technical specifics and business models, including project objectives, implementation processes, value propositions, and impacts (Figure 5.1: middle); and (c) stakeholder narratives and knowledge generation, covering lessons learnt and key actors involved (Figure 5.1 bottom). Each case study typically focused on a specific non-residential smart building, technology, or dataset.

Participants of Annex 81 and their extended networks, who had direct experience with decision-making or implementation of smart-building technologies, were invited to voluntarily contribute by completing the template. The coordinating team reviewed submitted case studies for completeness, consistency across different case studies, and clarity for non-technical audiences. When necessary, iterative exchanges with contributors occurred via email to refine content before final publication in the online repository. The web repository facilitates the dissemination of generated knowledge, providing associated visual resources (e.g., images, graphs, workflows) and supplementary materials such as building plans, models, dataset links, publications, and detailed project information where available.

5.2 Collected case studies

Eighteen case studies were collected and made available through the online repository, representing a diverse range of building types, applications, and locations across thirteen countries (Table 5.1). These case studies cover multiple technologies, such as model-predictive control (MPC), demand response (DR), open data platforms (OD), fault detection and diagnostics (FDD), and benchmarking (BM).

Project Information			
Continent:	☐ Europe ☐ Africa	☐ Asia ☐ North America	☐ Australia ☐ South America
City, Country:			
Building typology:	☐ Agriculture ☐ Community ☐ Education ☐ Hospitality ☐ Office ☐ Transport	☐ Arts and Leisure ☐ Defence ☐ Emergency ☐ Industry ☐ Retail (Shops) ☐ Utilities	☐ Commercial Offices ☐ Domestic (Residential) ☐ Health ☐ Miscellaneous ☐ Sport ☐ Warehouse
Technology installed/proposed:	☐ Model-based control ☐ Fault detection and diagnostics ☐ Energy benchmark ☐ Demand response ☐ Open data and data platform ☐ Other: **Please provide a brief description of the technology:**		
Data availability:			
Status:	☐ Design/Development ☐ Construction ☐ Testing/Commissioning ☐ Operational - awaiting results ☐ Operational - results available		

Description
Short introduction paragraph giving the context and a short description of the case study

Project aim
This section may include a short discussion on: a. Project design background; b. Project aims and objectives; c. Project motivation; d. The key technology to be/has been included.

Implementation
This section may include a short discussion on: a. General information for the building, the building services, and energy management system (if applicable); b. Data-driven approaches applied (e.g. improved control, FDD, etc.) (*if applicable*); c. Description of data requirements and data sources.

Value proposition
This section may include a short discussion on: a. Operational performance (e.g.: how well did it work, is it easy to use?); b. Significant benefits compared to traditional technologies/the past.

Impacts
This section may include a short discussion on: a. Benefits gained; b. Comparison to expectations; c. Reasons for any discrepancies; d. Scalability/Transferability.

Business Proposition/Business model
Discuss the business case, or potential business model for the innovation like: a. Annual contract for service? b. Software as a service? c. At-risk with shared savings? d. Install only (customer manages)? e. Other?

Lessons learnt
This section might include the following: a. Unsolved issues during/after the design, implementation and commission of the technologies; b. Lessons learned in the design, implementation and commission of the data-driven technologies; c. Occupant acceptance (complaints/endorsement); d. Challenges faced (e.g., delays, installation issues, commissioning problems, complexity, user complaints?) e. Unintended consequences (e.g., unexpected impact on other systems? Safety issues/ Reliability issues? Privacy/security risks?) f. Other concerns.

Key stakeholders (as appropriate)]	Information providers
Select one/some of the followings: ☐ Client ☐ Designers ☐ Consultants ☐ Manufacturers / Suppliers ☐ Contractors ☐ Monitoring and reporting ☐ Others (e.g., building operator / manager)	Who provided information for the case study and their role/perspective in this project?

Other information

For more information on the Case Study:

Contact person:	Name/E-mail address/Affiliation

Figure 5.1: Case study template.

Table 5.1: Summary of the collected case studies.

Case study	Location	Building type	Technical details
ZUB Building	Germany	Office	MPC, FDD
LBNL “Building 59”	U.S.A.	Office	MPC
OMV Head Office Building	Austria	Office	MPC
EV Building, Concordia University	Canada	Education	OD
Infineon R&D Building	Austria	Education, Office	MPC, FDD
CSIRO Synergy Building	Australia	Education, Office	MPC, OD
Holiday houses with swimming pools	Denmark	Recreational Residential Building	MPC, DR
Cooling Plant in a Factory	Japan	Industrial	FDD
The Post am Rochus Building	Austria	Office, Retail	MPC
Campus Inffeldgasse	Austria	Education, Office	FDD, DR
TU Delft “Building 28”	Netherlands	Education	FDD, OD
PoliTo Campus (Photovoltaic Plant)	Italy	Education	FDD
Varennes Net-Zero Energy Library (Building & Controls)	Canada	Library	MPC, DR
Varennes Net-Zero Energy Library (Energy Platform)	Canada	Library	DR, OD
LBNL “Smart Energy Analytics Campaign”	U.S.A.	Community, Education, Hospitality, Office, Retail, Offices, Health	FDD, BM
Semantic Application in Building Automation: Government Offices in Hong Kong	Hong Kong SAR	Miscellaneous (incl. Offices)	BM
HiLo Living Laboratory	Switzerland	Office	MPC, FDD, BM, DR, OD
New Museum of London Smart Building prototype	United Kingdom	Museum	FDD

Analysis of the collected case studies identified shared themes and unique characteristics of the implemented technologies, helping synthesise the main drivers and barriers to adopting data-driven smart buildings. The primary driver across these projects was consistent: reducing energy demand while maintaining or improving occupant comfort in both new and retrofitted buildings.

Many case studies introduced novel, data-driven prediction models at a whole building or individual component level to enhance building operation, improve prediction accuracy, and reduce commissioning efforts.

For instance, in the *CSIRO Synergy Building case study*, a machine-learning-enabled optimisation engine was integrated to adjust setpoints automatically for chiller plant control. Operational data stored in CSIRO’s data management platform were used to train machine learning models to forecast potential scenarios and optimise setpoints. The key advantages of this optimisation engine compared to traditional cooling controls include: a) transparent presentation of current performance metrics, recommended control strategies, and forecasted savings; b) straightforward implementation through cloud-based technology, utilising existing building management system (BMS) data; c) scalable, customised weather compensation control strategies informed by specific site knowledge; and d) cost-effectiveness, achieving a payback period of less than 12 months.

In the *EV Building case study*, the collected operational data was leveraged to create data-driven models that improved facility management decision-making. Machine learning clustering methods derived hourly occupancy patterns, generating realistic stochastic occupancy profiles. These profiles enhance simulations in software like EnergyPlus and enable better control strategies. This approach also improves accuracy in predicting electrical peak demands, allowing facility managers to implement effective peak-shifting strategies and reduce energy costs.

5.3 Thematic analysis of case studies and lessons learnt

Across all case studies, lessons learned revolved around four core themes: i) data quality and management, ii) technology specification and implementation, iii) stakeholder engagement, and iv) governance, compliance, and legal oversight (Table 5.2). These lessons learnt are discussed below.

Table 5.2: Thematic analysis of the reported lessons learnt for the eighteen case studies.

	ZUB Building	LBNL Building 59	OMV Head Office	EV Building	Infineon R&D Building	CSIRO Synergy Building	Holiday Houses with Swimming Pools	Cooling Plant in a Factory	Post am Rochus Building	Campus Inffeldgasse	TU Delft Building 28	PoliTo Campus (PV plant)	Varennes Library (Building & Controls)	Varennes Library (Energy Platform)	LBNL Smart Energy Analytics Campaing	Government Offices in Hong Kong	HiLo Living Laboratory	New Museum of London
Data quality and management																		
Data specification								✓										
Data collection, sensing and monitoring				✓			✓			✓		✓						
Data quality			✓		✓							✓						
Interoperability														✓		✓		
Data management	✓	✓				✓			✓			✓						✓
Technology specification and implementation																		
Computational requirements and complexity								✓										✓
Modelling and simulation			✓	✓	✓			✓	✓									
Model transferability								✓								✓		
Operational strategies	✓												✓					
Implications of the Covid-19 pandemic		✓				✓												
Technology deployment									✓					✓				
Stakeholders engagement																		
Industry acceptance								✓					✓					
Users' acceptance	✓													✓			✓	✓
Users' behaviour										✓								
Users' comfort		✓															✓	
Governance, compliance and legal oversight				✓					✓									

i. **Data quality and information management**: Specification of data requirements–such as the number of data streams to collect and the desired resolution, or relevant metadata to be collected–must be considered from the earliest design phase. This should be linked to the purpose this data will be used for (*Cooling Plant in a Factory case study*). Likewise, planning a thorough data collection strategy was deemed crucial to support dependable predictive modelling and to enable simulation with lower uncertainty. Achieving this requires (a) ensuring a varied and accurate range of data streams, such as detailed occupancy data and sub-metering (*EV Building, PoliTo Campus, and Campus Inffeldgasse case studies*); and (b) selecting widely adopted sensing and communication technologies that deliver consistent performance and long-term reliability (*Campus Inffeldgasse, PoliTo Campus, and Holiday Houses with Swimming Pool case studies*).

Accurate, reliable, and information-rich data was fundamental for smooth real-time simulations and data-driven predictive modelling (*OMV Head Office Building, Infineon R&D Building, PoliTo Campus, Factory Cooling Plant, and CSIRO Synergy Building case studies*). The belief that sensors will deliver correct values is often misplaced. This can be due to miswiring of sensors, sensor drift, lack of calibration, or even poor labelling. Using robust sensing technology, redundant acquisition strategies and modern infrastructure, with local data storage, helped mitigate the risks of data gaps caused by communication failures or connectivity loss. Ensuring data quality and completeness is key to supporting data-driven decision-making. This can be done manually or integrated directly within time-series databases (e.g., consistency checks, threshold-based cleaning, and data imputation if needed). For example, the *PoliTo Campus case study*, substantially reduced the percentage of missing data.

Integration and upkeep of non-interoperable data streams and metadata formats from different proprietary vendors or systems (e.g. lighting, access controls, or BMS) can be both time-intensive and costly, impeding smooth model development and real-time operation (*Government Offices in Hong Kong case study*). A significant effort was needed in the *LBNL Building 59 case study* to maintain consistent, high-quality data coming from many different platforms. Likewise, the *Varennes Library case study* encountered delays as it grappled with non-standard communication protocols and difficulties in integrating smart devices for its transactive energy system. Missing standard sensor information and lack of open data complicated the *ZUB Building case study's* approach, creating unexpected costs.

Clear data governance – especially through meaningful naming conventions (or renaming when refurbishing buildings) and utilising standardised metadata schemas – was identified as a cornerstone of sound data collection and storage (*New Museum of London case study*). Manually cataloguing metadata is time-consuming, often requiring multiple sources of knowledge (*CSIRO Synergy Building case study*). Therefore, an increasing focus on digitalisation is advocated for operational/telemetry data storage (e.g., automatically including location and relevant tags such as equipment hierarchy, make/model and serial numbers). Development of semantic data platforms that support semantic models (e.g. based on the Brick schema) and time-series databases can be used to effectively tackle this challenge by creating a digital representation of the system with standardised relationships to classify and interconnect its different components (*Government Offices in Hong Kong case study*).

ii. **Technology specification and implementation:** Many existing approaches can make specific, often limiting, assumptions about how each building operates (e.g., space utilisation, schedules, etc.). If the operating point changes, using past data might yield unexpected results. For example, during the pandemic the modus-operandi of buildings changed, requiring higher ventilation rates, leading to higher energy consumption (*LBNL Building 59 and CSIRO Synergy Building case studies*). These shifts made it harder to determine normal baselines or optimise future building performance using past data. The ability to operate when data is unavailable or conditions change, and respond to any unanticipated event, can lead to more resilient buildings.

Virtual building models can automatically detect common issues during building-services installation and commissioning, such as hydraulic or control-logic errors (*OMV Head Office and Infineon R&D Building case studies*). Inaccurate operating assumptions made at early stages, substitution of materials or components during construction, or operational changes can create significant deviations between design and operational performance. The fragmented nature of such changes can create unintended consequences. Information artefacts (e.g. knowledge graphs) or simulation models for what-if scenarios, require continuous updates to remain relevant (*Post am Rochus Building case study*). This requires both ongoing oversight and integration of the maintenance of these artefacts into day-to-day operations. Building on lessons from the *Post am Rochus Building case study*, some recommended steps for commissioning and trial phases include (i) defining coherent, system-wide control strategies and operational modes, (ii) developing clear documentation for commissioning of major components, and (iii) performing functional quality management at the component level. This enables each element's performance to be checked against design criteria, deviations rectified, and all systems verified to work together. Such efforts should persist during trial operations to sustain efficient performance, bolstered by close collaboration with control engineers when testing main operational modes and procedures.

The time needed to (i) configure and tune complex models reliably, (ii) spot and fix bugs, (iii) perform plausibility checks, and (iv) arrange suitable data visualisation, can become problematic when decisions are time-sensitive and additional delays often result in extra costs. Likewise, the implementation effort for simulation models, like the ones used for automated FDD, can be expensive and may not yield enough direct payback on their own (*Factory Cooling Plant case study*). Thus, the ability to develop and deliver portable and reusable applications (Mavrokapnidis *et al.*, 2023) is important, in order to reduce effort in bespoke development of such applications and improve re-use, reducing the cost and implementation time compared to more traditional approaches where customised models have to be extensively redeveloped and adapted. The use of AI and machine learning methodologies, leveraging knowledge acquired from previous tasks, successfully enabled model transferability as demonstrated in both the *HiLo* and the *Government Offices in Hong Kong case studies*.

Computational requirements and complexity of the system can also pose challenges to smooth and stable operation of the technology deployed. For example, issues were faced in the *Cooling Plant in a Factory case study* due to data loss between field devices and the cloud storage, power outages for inspections, or unexpected operating system updates. Similarly, issues were faced in the initial stages of the *New Museum of London case study*, such as getting the building management system on IP controllers and restarting network machines after updates. Lastly, the energy requirements for running ICT equipment and infrastructure should be properly considered in techno-economic feasibility analyses before implementing such systems.

iii. **Effective stakeholder engagement** is required for successful implementation of smart technologies. It is essential to clearly communicate the technology's benefits and capabilities to all stakeholders early in the project, building trust, encouraging cooperation, and managing expectations. Equally important is carefully addressing user needs to ensure their acceptance and satisfaction. As highlighted in the *Factory Cooling Plant and Campus Inffeldgasse case studies*, stakeholder training and knowledge transfer were particularly beneficial. These measures help on-site operators better interpret system results and encourage occupants to interact with the system as intended (for example, preferring mechanical ventilation over opening windows).

   Experience from the *ZUB Building case study* further illustrates that occupants tend to resist fully automated systems when direct control or overrides are unavailable. Perceived lack of control often causes dissatisfaction (Parkinson, 2023). Additionally, occupants were more receptive to automated setpoint adjustments when changes occurred unnoticed, such as leveraging thermal mass, rather than through noticeable or disruptive actions like motor-driven adjustments.

iv. **Governance, compliance, and legal oversight** requires attention when implementing data-driven smart technologies. For instance, the *Post am Rochus case study* identified a need for clear regulations specifying how to handle updates to design simulations and assumptions during construction, such as recalibrating models to match actual as-built conditions and validating them using monitored data. Additionally, legal challenges emerged regarding operator contracts that typically include energy-saving targets. These targets are often based on relative savings compared to a baseline period within the first three to five years of operation, which may not accurately reflect long-term performance improvements. Lastly, collecting occupancy data through counting occupants raised unresolved privacy concerns related to GDPR compliance in Canada's *EV Building case study*.

In summary, valuable insights and lessons have been collected across various panel discussions and from the recorded case studies. A common reported barrier was the lack of openly accessible data from real-world implementations and limited standardisation in areas such as metadata cataloguing, data labelling, and interoperability. This absence of standards frequently results in ad hoc or proprietary solutions, limiting the exchange and reuse of potentially valuable information.

The eighteen analysed case studies consistently emphasised the importance of data quality and systematic data collection, as these directly influence the effectiveness of data-driven algorithms, the accuracy of information extraction, predictive reliability, and overall costs.

Other challenges included the lack of (i) clear narratives, (ii) detailed examples of real-world technical implementations, and (iii) unclear articulation of the value propositions. These collectively hinder wider adoption.

Stakeholders also highlighted that conservative industry structures, fragmented skill sets, and a tendency toward siloed thinking significantly limit the dissemination of best practices and knowledge-sharing. To address these issues, occupant training and engagement were recognised as essential for familiarising users with optimal operation practices and demonstrating the benefits of smart-building technologies.

The case studies created within Annex 81 can help substantiate the benefits (e.g., reduced costs, enhanced comfort, improved fault management) and stimulate further research and innovation activities.

It was also recognised that concerns about loss of user control, cybersecurity, privacy, and legal implications associated with new data-driven technologies—such as handling revisions to operational agreements—must be clearly addressed or refined. Resolving these issues is crucial to increasing stakeholder confidence and accelerating the widespread adoption of smart-building solutions.

6. Supporting Further Adoption of Data-Driven Smart Buildings

Data-driven smart buildings is an emerging technology class with great potential to drive energy productivity in buildings. Estimates of the benefits of digitally enabled efficiency and demand flexibility, in different regions, include:

- *Across Europe over a 20-year period*: building automation technology could be ramped up progressively to achieve energy savings of 13%, compared with the reference scenario, with estimated cumulative 3.4 GT of CO_2 emissions savings (Waide et al, 2013).
- *Across the USA over the period 2021 to 2040*: The US Department of Energy (2021) estimates that 'Grid-Interactive Efficient Buildings' (GEBs) have the potential to reduce total U.S. electricity supply costs by 2 to 6% (saving the US power system $100-200 billion) and help to reduce CO_2 emissions by around 6% (saving around 80 MT/year of CO_2 emissions).
- *Across the Australian National Electricity Market to 2040*: demand flexibility could provide $18b in cost savings (ARENA, 2022).

Noting the significant scale of these benefits, the rationale for policy action to support further adoption of data-driven smart buildings is both:

In the short term, support digitalisation in buildings because it's an underutilized energy efficiency technology class, that can be part of a no-regrets (positive benefit to cost ratio) policy approach for reducing greenhouse gas emissions.

In the medium term, support digitalisation because it will become a critical tool for enabling the clean energy transition. Vast amounts of new variable renewable electricity resources will need to be backed up with controllable (dispatchable) resources to maintain electricity system reliability, and to avoid discarding otherwise unusable renewable energy production. Dispatchability and electricity system coordination will require digitalisation.

Navigating the clean energy transition will require zero-carbon-ready buildings to be 'digital ready'.

It is no surprise then, that the IEA identified '*Leveraging digital innovation to enhance system-wide efficiency*' as one of its ten strategic principles for achieving the COP28 goals (IEA, 2022).

Policy actions to realise the potential of digital technologies can focus on both stimulating innovation and reducing barriers to adoption.

In support of these policy actions, Annex 81 focused its research on (i) stimulating innovation by running data-driven artificial intelligence (AI) competitions and (ii) consulting with industry to identify barriers and develop policy solutions to overcome them. The results of this research are discussed in the following subsections.

6.1 AI Competitions

Crowd-sourced data science competitions are a powerful tool for advancing research in energy informatics, and for developing innovative machine learning solutions. Over the past decade, competition platforms (e.g., Kaggle, AI Crowd and others) have become popular, as a way of tackling complex data problems, by harnessing the collective intelligence of global participants. Such competitions are a cost-effective alternative to traditional in-house R&D, often yielding creative solutions from diverse teams around the world. They also provide valuable learning opportunities for participants to sharpen their skills and to contribute to solving real-world challenges.

These competitions typically involve release of ground-truth data to competitors, to enable them to train their machine learning algorithms. Subsequently, new data is released (without ground truth) to see how well the algorithms perform. The best performing algorithm wins (based on CVRMSE or other statistical accuracy KPI).

In the energy sector, data competitions have been used to address problems ranging from energy efficiency optimization to renewable integration and grid stability. Competitions can include both quantitative and qualitative elements, assessing solution merit using criteria relating anywhere from mathematical excellence to business model potential.

Relevant recent competition topics include

- **Building load forecasting**: (1) ASHRAE Great Energy Predictor III (Miller et al, 2020), (2) BigDEAL Forecasting peak timing of electricity demand (Shukla and Hong, 2024) and (3) Global AI Challenge (Hong Kong EMSD, https://2021.globalaichallenge.com/en/home)
- **Grid-interactive optimization of neighbourhood energy consumption**: (1) CityLearn 2022 (Nweye et al, 2022),
- **Data-driven application innovation**: (1) NYSERDA RTEM Global Energy & Building Hackathon 2022, (https://be-exchange.org/nyserda-rtem-hackathon-demo-day/)
- **Classification of sensor metadata**: (1) Brick by Brick 2024 (https://d3qvx1ggyg4lu1.cloudfront.net/challenges/brick-by-brick-2024)

By way of example, the ASHRAE Great Energy Predictor III challenge (Miller et al, 2020) required competitors to find the most accurate modelling solutions for predicting future building energy consumption, based on historic weather and consumption data. Competitors were provided with over 20 million points of training data from 2,380 energy meters collected from 1,448 buildings. The data was obtained from 16 sources. The competition had 4,370 participants, split across 3,614 teams from 94 countries who submitted 39,403 predictions. Competitors publicly shared 415 reproducible online machine learning workflow examples (notebooks), including over 40 additional full solutions. This provides an unprecedented evidence base to draw general conclusions from (relating to what works best for this challenge task). In this competition, the most popular and accurate machine learning workflows used large ensembles of mostly gradient boosting tree models, such as LightGBM. Preprocessing of the data sets emerged as a key differentiator of the best performing solutions.

Key elements of hosting a competition include dataset collection and curation, participant engagement, and competition design (both from an implementation perspective and from an industry relevance/ real-world-impact perspective).

Annex 81 ADRENALIN Competitions

With funding support from ERA-Net Smart Energy Systems, the ADRENALIN (dAta-DRivEN smArt buiLdINgs) project was a consortium of 12 project partners (linked to Annex 81), that organised two AI competitions. The project aimed to (i) create a data sandbox, (ii) run AI competitions using the data sandbox, and (iii) support transfer of AI software algorithms to industry for implementation. The project included 6 academic partners and 6 industry partners across 7 countries. The two competitions were

1. The ADRENALIN Load Disaggregation Challenge: This challenge required competitors to develop machine learning or statistical models that could take a building's site-level energy consumption meter data and disaggregate it, to quantify the energy consumption of the building's HVAC-related loads (i.e its constituent temperature-dependent energy consumption). If successful, this application could avoid the need for expensive submetering of HVAC equipment. It could also help evaluate the benefits of various energy efficiency solutions (e.g. addressing sub-optimal insulation or aging HVAC equipment).

The dataset assembled for the challenge comprised data from multiple buildings in different countries, contributed by the various project partners. These buildings included commercial and public facilities (e.g., office buildings, kindergartens), which ensured that no personally identifiable consumer data was involved. For each building, the dataset included the main meter measurements (overall electricity or heating consumption) as well as sub-metered readings for the key temperature-dependent loads (such as heating/cooling systems), which served as the ground truth for disaggregation. In addition to energy meter readings, the dataset provided contextual features: basic building attributes (e.g., floor area, building type) and local weather data (e.g., outdoor temperature) synchronized with the consumption data.

The challenge attracted 47 participants and resulted in 13 valid submissions. 9 submissions successfully exceeded the minimum performance threshold set by the organisers.

2. BOPTEST Smart Building HVAC Control Challenge: This challenge required competitors to develop control algorithms that can activate the flexibility potential of a building's HVAC system - based on variable cost signals, while not compromising indoor air quality. The winning entry would have the lowest weighted score (compared with the price ignorant baseline controller). The weighted score included components relating to (i) annual energy cost, (ii) peak energy demand and (iii) indoor environment (including both CO_2 concentration levels in the occupied space and Kelvin-hours of thermal discomfort).

   The competition was implemented using the BOPTEST framework, as a means of benchmarking each competitor's results on a like for like basis, using virtual building emulators, and using the BOPTEST "highly dynamic" energy price scenario.

   In addition to submitting controller performance data, the final submission required participants to submit a description of their control approach. As a result, there was both quantitative and qualitative components to the final assessment.

   The challenge attracted 22 participants and resulted in 5 valid submissions. 4 submissions successfully exceeded the minimum performance threshold set by the organisers.

Each winning team received a prize of 10,000 euros, distributed in two instalments: the first 5,000 euros awarded immediately upon announcement of the winners and the second 5,000 euros paid after a three-month knowledge transfer period with the sponsoring companies.

There were a number of learnings from organising these competitions. These are discussed by Tolnai *et al*., 2025. Some of these learnings include:

Data quality and preparation is challenging: As the dataset was compiled from multiple real buildings via different project partners, harmonizing it required extensive preprocessing. Issues such as inconsistent formats, missing values, and varying sensor accuracies surfaced throughout the data curation process.

Generalisability needs careful consideration for industry implementation: Designing the competition to return a single aggregated score, that combines results across all buildings, helped to prevent participants from overfitting to individual buildings. This can help ensure that models are capable of performing well across diverse conditions. Similarly, selection of KPI metrics is critical to avoid inadvertently creating prediction biases. The computational cost of complex models would ideally be incorporated into the assessment KPIs, particularly where near real-time applications are being considered.

One of the most valuable outcomes of competitions is the dissemination of knowledge. Competitions should generally require open-source solutions (with appropriate licensing) and should host post-competition workshops where winners can explain their methods.

Relatedly, solution transfer to industry should form part of competition design. ADRENALIN encouraged this by requiring a post-competition collaboration period for winning teams, ensuring that top solutions were properly documented and tested for industry use. Competitions could also consider offering follow-up grants or research funding for the top solutions, encouraging continued development and real-world piloting.

6.2 Barriers to Data-Driven Smart Buildings

Annex 81 participants conducted significant research attempting to understand the barriers that might be impeding industry uptake of data-driven smart building technology.

Initial Scan

An online discussion between Annex 81 participants, and invited industry participants, provided an initial qualitative scan of current industry practices, stakeholder needs, and implementation challenges. Several critical issues emerged (Figure 6.1), including: (i) unclear value propositions, poorly aligned with stakeholder needs and existing processes; (ii) ill-defined implementation pathways, including uncertain business case and incentives; (iii) limited real-world evidence of successful smart technology implementations; (iv) insufficient standardisation; (v) inadequate availability of high-quality data and metadata necessary for credible data-driven applications; and (vi) actual and perceived legal and ethical concerns.

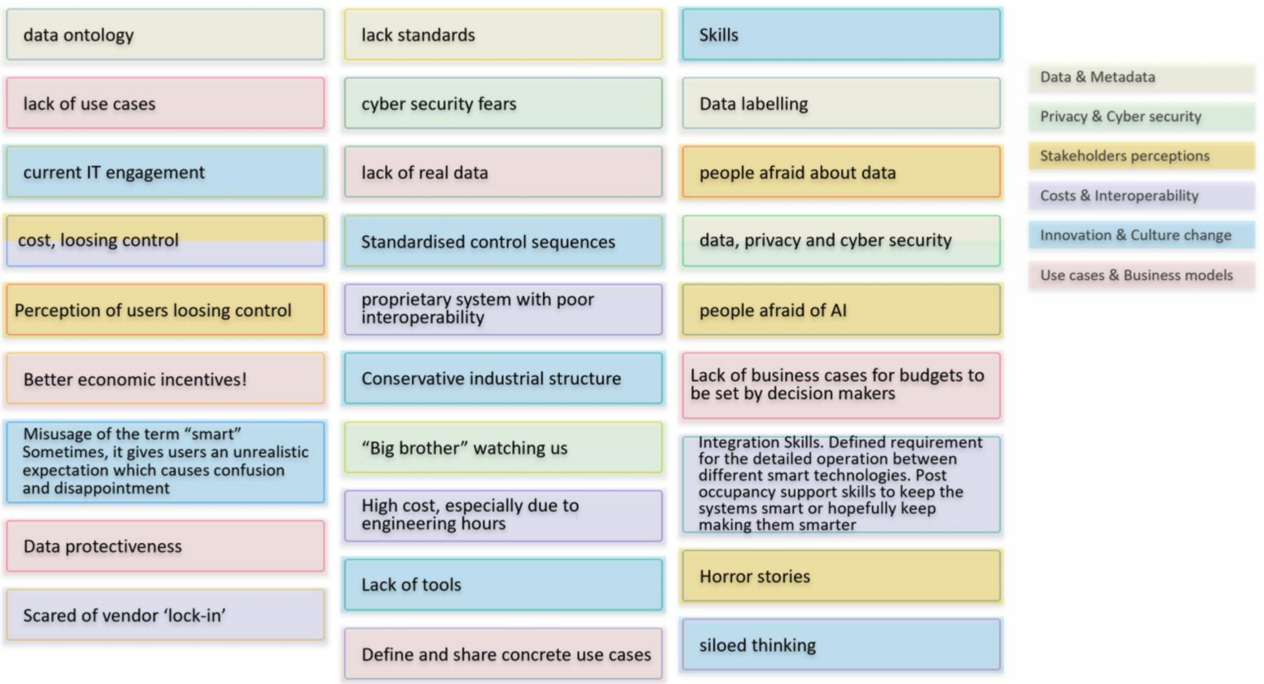

Figure 6.1: Annex 81 Stakeholders' perspectives on barriers to smart buildings implementation.

To address these barriers effectively, participants were asked how Annex 81 activities could contribute to overcoming innovation and technology uptake challenges. Participants emphasised several actions critical for accelerating adoption. They strongly advocated for (i) knowledge-sharing platforms, particularly to promote best-practices using practical examples and detailed case studies to clearly demonstrate successful implementation pathways, (ii) promotion of standards, and (iii) access to data. Participants emphasised the need for reliable, high-quality data and metadata, streamlined implementation methodologies (such as data labelling and control sequences), and enhanced interoperability.

A more detailed survey was conducted on barriers relating to data. The results of this survey are illustrated in Figure 3.7 and discussed in Section 3.2.1 of this report.

FDD Barriers Mapping

Further survey research and literature reviews were undertaken, focusing specifically on the industry barriers relating to the Fault Detection and Diagnosis (FDD) application (Chen *et al.*, 2023, Andersen *et al.*, 2024, Melgaard *et al.*, 2022).

Barriers were mapped across (i) the various stages of the FDD life-cycle (Figure 6.2), and (ii) the relevant stakeholder to which the barrier applies. The barriers were divided into five barrier categories:

- **Economic and business:** Costs and benefits for end-users and/or business limitations.
- **Technological and technical:** Technical knowledge, interoperability, infrastructure and/or data.
- **User-related:** User experience, interface and/or misunderstanding.
- **Regulatory:** Policies, GDPR and/or cybersecurity.
- **Social and societal:** Cultural, community and stakeholders, benefits for society and/or environmental sustainability.

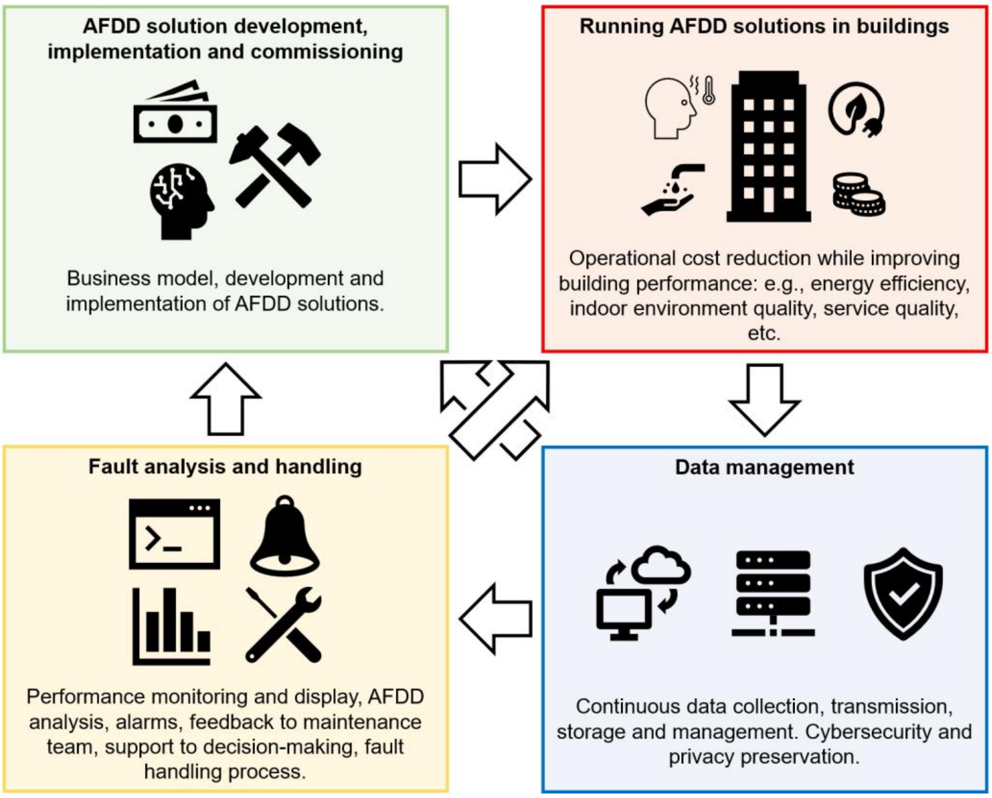

Figure 6.2: Mapping of the AFDD ecosystem for implementation and operation of AFDD solutions.

Key barriers relating to the identified stakeholders are:

- **Building Technology industry (AFDD companies + BMS vendors).** The key issues affecting this category typically relate to implementation in buildings, and mostly relate to *interoperability* and to *market related issues and adoption*. Legacy BMS systems and proprietary communication protocols, in existing buildings, challenge the implementation of new FDD products. This makes integration not only technically difficult but requires a significant investment that may not match the customer's expectations.

- **Building owners.** Such stakeholders might be required to make large investments to upgrade or retrofit their existing equipment. Implementing advanced FDD tools may expose the building systems and data to cybersecurity issues. Without a broadly accepted methodology to assess the potential performance of FDD tools in operation, calculation of investment KPIs (like return on investment or payback time) may be problematic, and it could be difficult to estimate potential savings.

- **End users (maintenance staff).** Lack of interpretability or transparency behind the results of FDD tools may lead to difficulty in accepting results (fault root causes, diagnosis, actions to be taken) from the end user perspective. Users are often interested in fully understanding how the tool calculates a certain result or prioritizes the intervention on a certain fault. Along with trust issues and the learning curve required to understand and use such tools, the end users may be reluctant to change day-to-day operations in favour of new procedures.

A detailed breakdown of the barriers, relating to FDD, is provided in the Annex 81 Subtask C report (Wen *et al.*, 2025).

Further Literature on Barriers

Annex 81 research identified further, more general, literature on barriers to the adoption of digitalisation in buildings, such as that by the IEA (2021), the Digitalisation Working Group of the Energy Efficiency Hub (Otte *et al*., 2022) and the US Department of Energy (2021). These studies highlight similar barriers of (i) Interoperability, (ii) Data access, (iii) Privacy and (iv) Cyber Security.

Trianni *et al.* (2022) conducted focus group research to further understand the barriers experienced by industry practitioners. Barriers were ranked in importance for each of four categories. The rankings are illustrated in Figure 6.3.

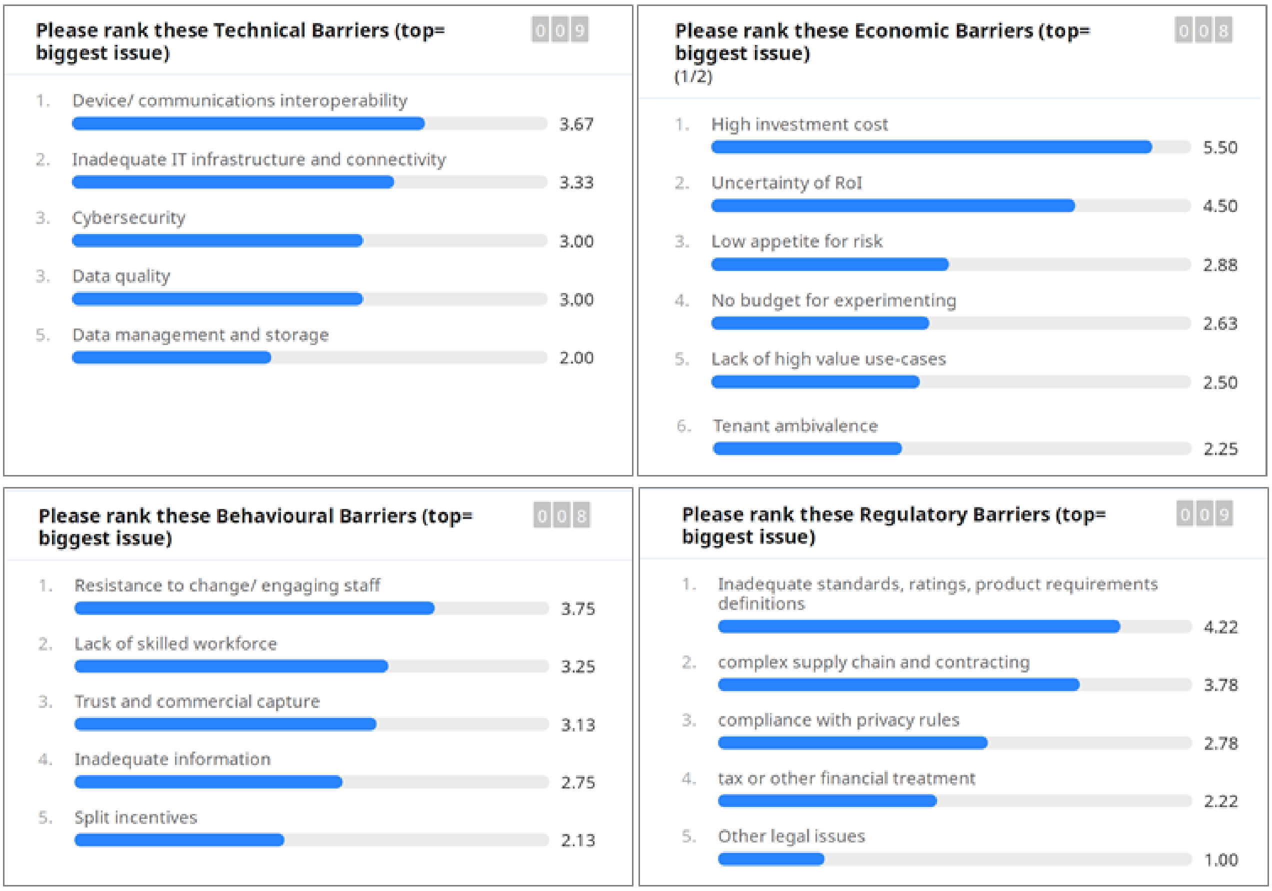

Figure 6.3: Ranking the importance of barriers to utilising digitalisation for improving energy performance (Source: Trianni *et al.*, 2022).

These rankings demonstrate a tendency for industry to reframe the barriers in terms of the attractiveness of the investment or 'the business-case'. They found that most of the challenges with the business case could be grouped under two core (but connected) themes:

- Uncertain Return on Investment: Despite the proven short payback-time, industry perceives the cost of retrofitting IT infrastructure and digital connectivity to be high, and the returns uncertain. This reflects the highly variable cost of implementing the technology, which can depend on existing controls hardware capability (e.g. legacy systems, interoperability issues, etc) and the commercial context of the investment (e.g. supplier work-scope and liability allocation, bundling with other upgrades, etc), amongst other things. The benefits can also vary significantly, depending on how well the building is currently performing (i.e. a poorly performing building has more scope for improvement). Upfront investment is needed to quantify both the costs and the benefits, without any a-priori guarantee that the business case will 'stack-up'. This uncertainty leads to a reluctance to even start the process of exploring the viability of digital energy productivity opportunities.

- Complexity and Trust: Industry perceives digitalisation as a complex product to purchase and implement. Various software and hardware 'layers' make up the 'product stack'. Furthermore, implementing the technology can often require changes in work-force practices (to take advantage of the insights obtained from the technology). Industry expressed a desire for more guidance on product requirements, and for common terminology that can help to simplify purchasing, avoid potential pitfalls, and enhance competition.

6.3 Potential Solutions to Identified barriers

Various roadmaps have proposed solutions for addressing barriers to digitalisation and digital energy productivity solutions. These roadmaps aim both to unlock energy savings and to enable buildings to participate, as flexible distributed energy resources, in the clean energy transition. Relevant recommendations, from a sample of these roadmaps, are summarised in Table 6.1.

These roadmaps converge on the need for government to play a coordinating role, to support adoption of digitalisation in buildings. They particularly identify the need to focus on activating digitally-enabled demand response resources. Commonly cited areas for possible policy development include:

- Provide guidance and certification tools, as a means of simplifying the purchase of digital infrastructure and to help manage risk.
- Set 'digital-ready' expectations through mandatory data collection and reporting requirements, and by including digital infrastructure requirements in construction codes for new buildings,
- Enable improved access to energy markets,
- Incentivise both innovators and pilot demonstrations by early adopters, and
- Provide support for industry capability and capacity building

Industry Interviews: Potential Policy Solutions to Accelerate Adoption of Data Driven Smart Buildings

Annex 81 participants interviewed leading industry practitioners to further understand industry pain points and aspirations. Sixteen interviews were conducted, representing industry perspectives across Europe, North America, and Asia-Pacific. Interviewed stakeholders included Software-as-a-Service (SaaS) platform providers, design consultants, building owners, hardware suppliers and an energy retailer. Results of these interviews, and the resulting policy solutions formulation, are detailed in White *et al.* (2024).

The interviews generally identified a strong industry desire to use digitalisation technology as a tool for achieving sustainability goals, particularly where it is cost-effective and simple to implement. These motivations were particularly driven by a desire for improved building ratings, to comply with the corporate ESG policies of stakeholders (including tenants) and a desire to satisfy compliance responsibilities.

Consolidating all the relevant information sources, a range of policy solutions were formulated and tested with the industry representatives. The policy solutions were categorised under eight themes and a 'Policy Package' was developed (Figure 6.4) for driving adoption of digitalisation as a means of optimising energy use in buildings

The solution themes in the 'Policy Package for Energy Optimisation in Buildings through Digitalisation' are:

Theme 1: Provide Information – to reduce complexity and information asymmetry for buyers.

Theme 2: Establish 'digital ready' certification – to standardise solutions and recognise achievement.

Theme 3: Lead by example – to provide a cohort of early adopters that catalyse the market.

Theme 4: Support researchers and innovators – to catalyse a wider range of product offerings, increase industry maturity, and provide independent validation of the benefits of digitalisation.

Theme 5: Incentivise EMIS technology – to improve the return on investment from the technology.

Theme 6: Reduce data sharing risk – to improve certainty and manage possible compliance issues.

Theme 7: Build workforce skills and capacity – to be able to deliver the services at scale.

Theme 8: Integrate buildings into the electricity system – to prioritise the clean energy transition.

Table 6.1: Summary of existing roadmaps and the solutions they propose

	IEA (2021) "Energy Efficiency 2021"	**EE Hub (2022)** "Roadmap on Digitalisation for Energy Efficiency in Buildings"	**IE 4E (2022)** "Interoperability"	**US DoE (2021)** "Grid Interactive Efficient Buildings Roadmap"	**Green Building Council of Australia (2023)** "From Net Zero to Zero"
Roadmap Focus / **Barrier**	Advocate for policies that enable innovative energy efficiency solutions and drive system-level benefits for the clean energy transition	Address barriers to implementing digitalisation policies and programs that drive energy efficiency in buildings	Understand the impact of IoT device level interoperability on efficiency and demand Flexibility.	Ensure a robust portfolio of flexible and cost-effective resources to navigate the clean energy transition.	Develop a set of principles and actions that align economic and environmental outcomes for building owners
Interoperability	✓ Remove interoperability barriers	✓ Develop policies that utilise interoperability standards. Require clear communications protocols between consumers and external markets	✓ Minimum interoperability requirements for flexible appliances (thermostats, pool pumps, heaters etc) Informatory labelling for interoperability capability. Incentivise interoperable devices. Develop/adopt standards.	✓ Accelerate adoption of existing open standards. Require system and device level reporting capabilities. Explore methods to rate or score interoperability of devices and buildings	
Data Access	✓ Provide (i) supportive institutional arrangements and (ii) access to data platform infrastructure	✓ Equip consumers with actionable energy use information. Provide infrastructure for sharing meter data and energy system data. Incentivise improved data availability, quality, and analysis		✓ Develop standard metrics and methods for data collection, data analysis, and measurement and verification (M&V) of demand flexibility. Enhance existing building performance tools to include demand flexibility and GHG emissions information. Integrate EE data and communications standards requirements with grid-interactive standards	✓ Introduce requirement for grid-interactive functionality in buildings as part of building construction codes. Develop a digital strategy for the integration of buildings as distributed energy resource (DER) nodes in the electricity system through better use of data flows and appropriate software.

	IEA (2021) "Energy Efficiency 2021"	**EE Hub (2022)** "Roadmap on Digitalisation for Energy Efficiency in Buildings"	**IE 4E (2022)** "Interoperability"	**US DoE (2021)** "Grid Interactive Efficient Buildings Roadmap"	**Green Building Council of Australia (2023)** "From Net Zero to Zero"
Cybersecurity and Privacy	✓ Ensure adequate protection from cyber security and data privacy risks through frameworks and guidelines	✓ Create a cybersecurity certification process. Enact data handling regulations that include data protection, data security, and data sovereignty		✓ Enable users to provide control permissions to trusted third-party applications and services while ensuring cybersecure controls and communications	
Return on Investment	✓ Ensure energy markets value the services provided by digital energy efficiency. Utilise digitalisation to streamline measurement and verification of energy efficiency and flexibility			✓ Provide incentive mechanisms to encourage investment in demand side programs. Consider customer adoption of EE and demand flexibility as part of tariff design objectives. Package demand flexibility with other consumer offerings. Identify opportunities for improving demand flexibility access to wholesale markets. Increase consideration of non-wires solutions Incentivise demand flexibility through energy performance contracting	✓ Explore how incentives or rating programs can be used to incentivise grid-interactive solutions in the built environment. Introduce obligations for retailers to engage with and support customers on active efficiency measures. Explore how to improve current carbon certificate schemes to add time-of-use (and ideally real time) carbon information.
Complexity and Trust	✓ Increase stakeholder awareness and trust in digital technology and infrastructure			✓ Research and socialize data on demand flexibility programs and operation experiences: including data on the hard and soft costs of advanced sensing and control technologies.	✓ Provide clear communication, and education to promote opportunities for testing and delivering grid-interactive efficient buildings at scale.

	IEA (2021) “Energy Efficiency 2021”	**EE Hub (2022)** “Roadmap on Digitalisation for Energy Efficiency in Buildings”	**IE 4E (2022)** “Interoperability”	**US DoE (2021)** “Grid Interactive Efficient Buildings Roadmap”	**Green Building Council of Australia (2023)** “From Net Zero to Zero”
				Design and market demand flexibility programs with a focus on consumer preferences. Provide technical assistance. Government to participate in DR and EE programs and markets with their own buildings.	
Digital skills	✓ Provide training programmes that include digital skills.			✓ Establish skills standards and creden-tials relevant to advanced building technologies and operations. Broaden relevant workforce develop-ment programs. Establish building training and assess-ment centers.	
Technology and business model innovation	✓ Provide finance for pilots and demonstration projects. Provide funding for start-ups, and remove barriers for new market entrants		✓ Provide an open platform environment to support private sector IoT technology innovation.	✓ Support development and field testing of integrated whole-building control and grid service delivery. Develop and demonstrate integrated low-carbon building retrofit packages. Encourage and publicize innovative demand flexibility programs and pilots.	✓ Pilot digitalisation technologies and establish a program to implement digitalisation technology and demand flexibility in government buildings. Undertake research to understand further opportunities for grid-interactive efficient buildings

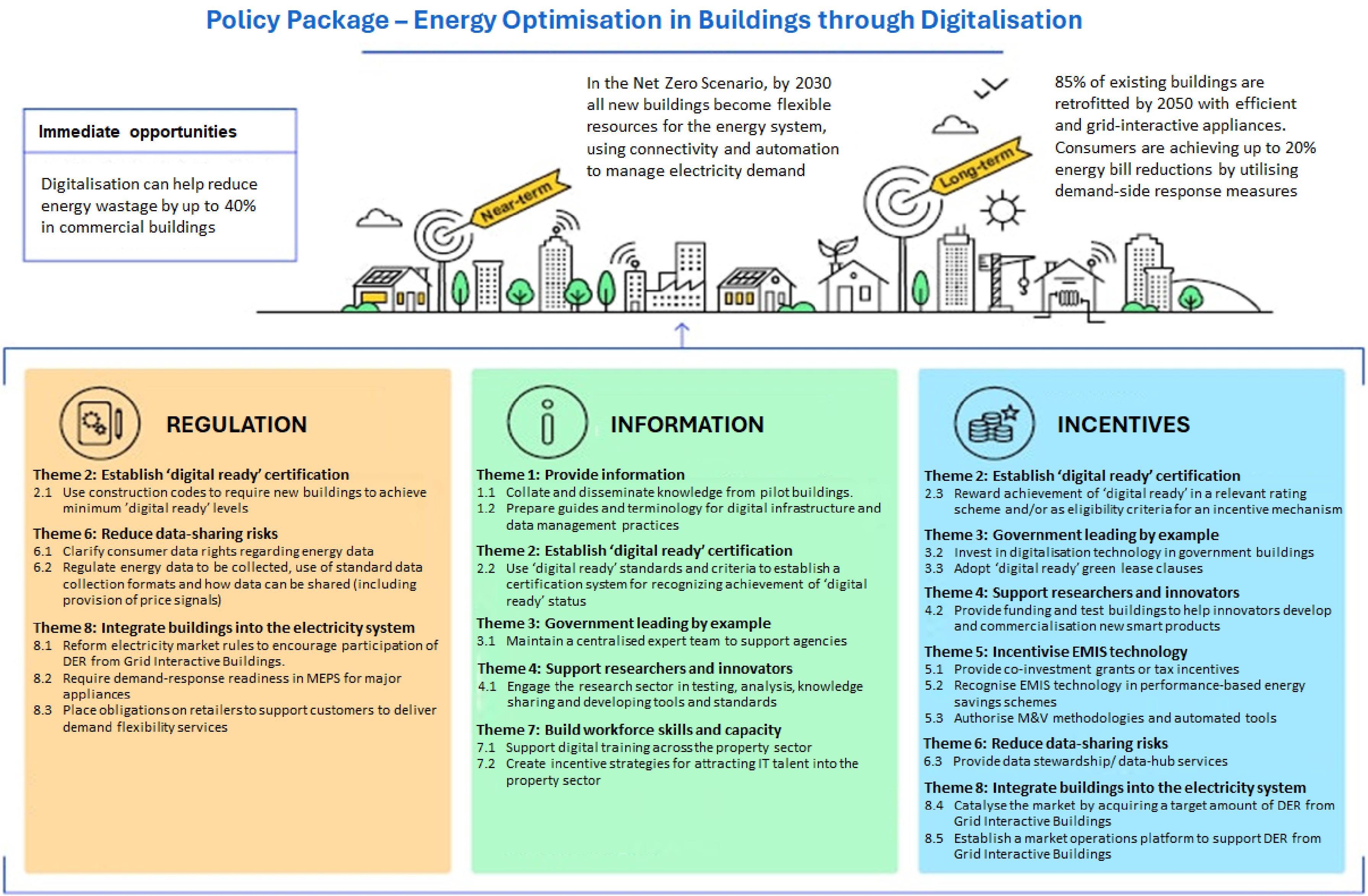

Figure 6.4: Policy Package for Energy Optimisation in Buildings through Digitalisation (format adopted from IEA Energy Efficiency Policy Toolkit, 2023).

Specific policy interventions under each of these themes are identified by White *et al.* (2024), and examples are given of how these policy interventions have been successfully implemented in different jurisdictions.

Actions under these themes are generally complimentary, supporting common strategic goals (impact pathways) to address key industry barriers. Some of these impact pathways are detailed in Table 6.2

Table 6.2: Recommended policy actions and their impact pathway

Barrier	Policy Action	Impact Pathway
Information and implementation complexity barriers	2.1 Collate and disseminate knowledge from pilot buildings 2.2 Prepare guides and terminology for digital infrastructure and data management practices 3.1 Maintain a centralised expert team to support agencies 3.2 Invest in digitalisation technology in government buildings 4.1 Engage the research sector in testing, analysis, knowledge sharing and developing tools and standards 4.2 Provide funding and test buildings to help innovators develop and commercialise new smart products 5.1 Provide co-investment grants or tax incentives	Industry requested more information to reduce technical and investment uncertainty - particularly in the form of case-studies and real-world evidence of successful smart technology implementations. This is best achieved by providing grant funding for case-studies and pilot implementations (Action 4.2, Action 5.1) at scale. Funding for these case studies should be contingent on thorough knowledge sharing using independent research bodies (Action 4.1). Knowledge should be consolidated and shared through established professional channels, with media tailored to the needs of decision makers (Action 1.1). Where possible knowledge should be synthesised into relevant guides and standards that de-risk implementation (Action 1.2). Government can play a key role in creating these information resources by investing in digitalisation technology across its own building portfolio (Action 3.2) and sharing the resulting knowledge. Government should recruit a specialist centralised team with digitalisation expertise (Action 3.1), to support (de-risk) implementation in its own buildings, and to ensure that there is appropriate expert knowledge sharing. The NYSERDA 'Real Time Energy Management' (RTEM) Program is an example of a successful knowledge sharing program. The RTEM Program provided a cost-share subsidy on systems, delivered through a panel of 'RTEM Qualified Vendors'. The technology was implemented in over 1,200 buildings covering ~27.5million m^2 of building floor area.

Barrier	Policy Action	Impact Pathway
Interoperability and data access barriers	1.2 Prepare guides and terminology for digital infrastructure and data management practices 2.1 Use construction codes to require new buildings to achieve minimum 'digital ready' levels. 2.2 Use 'digital ready' standards and criteria to establish a certification system for recognizing achievement of 'digital ready' status. 2.3 Reward achievement of 'digital ready' in a relevant rating scheme and/or as eligibility criteria for an incentive mechanism. 3.3 Adopt 'digital ready' green lease clauses: 6.1 Clarify consumer data rights regarding energy data 6.2 Regulate energy data to be collected, use of standard data collection formats and how data can be shared 6.3 Provide data stewardship/ data-hub services: 8.2 Require demand-response readiness in MEPS for major ap-pliances 8.5 Establish a market operations platform to support DER from Grid Interactive Buildings	Virtually all studies on industry barriers point to issues relating to proprietary systems that are incompatable and/or unable to provide requisite data. Industry requested more standardisation and greater clarity on the specific data that systems must be able to provide. Standardisation begins with the use of common language. This can be achieved by publishing guides with clear terminology to describe best practice digitalisation concepts (Action 1.2). These concepts can be further enshrined as standards and/or requirements specifications. Industry adoption would then be driven by including these requirements in construction codes (Action 2.1), certification/rating schemes (Action 2.2), incentive schemes (Action 2.3) and/or mandatory equipment specifications (Action 8.2). Government can play a key role in driving critical mass industry adoption of relevant voluntary schemes by, for example, adopting digital ready clauses for its own buildings (e.g. through 'green-leases' (Action 3.3)). Relevant rating schemes, incentive schemes and/or markets will require certain data inputs. Regulatory support should be given, to ensure that these data inputs are available as standard (Action 6.1, Action 6.2), and not subject to privacy concerns. Government operated data platforms (linked to relevant government schemes) can play a key role in supporting efficient and scalable collection of standard data from industry (Action 6.3, Action 8.5). The Green Button initiative is an example of a successful data sharing mechanism, that is providing over 60 million homes and businesses with secure access to their own energy information in a standard consumer-friendly and computer-friendly format. It can be used by consumers to choose their preferred retailer and to access energy saving advice through third-party companies and Apps. Center Denmark is an example of a not-for-profit independent company, providing digital infrastructure and data-stewardship services that support innovative new data-driven solutions. In partnership with Danish energy utilities, Center Denmark curates a data platform with daily energy data from more than 200,000 Danish households.

Barrier	Policy Action	Impact Pathway
Economic and first cost sensitivity barriers	2.3 Reward achievement of 'digital ready' in a relevant rating scheme and/or as eligibility criteria for an incentive mechanism. 3.3 Invest in digitalisation technology in government buildings 5.1 Provide co-investment grants or tax incentives. 5.2 Recognise EMIS technology in performance-based energy savings schemes. 5.3 Authorise M&V methodologies and automated tools: 8.1 Reform electricity market rules to encourage participation of DER from Grid Interactive Buildings 8.3 Place obligations on retailers to support customers to deliver demand flexibility services 8.4 Catalyse the market by acquiring a target amount of DER from Grid Interactive Buildings:	Despite proven short payback-times (in various scenarios), industry is seeking greater investment certainty and greater financial recognition for the range of benefits that digitalisation can bring across diverse use-cases. Particularly, there should be a level-playing field for grid integrated buildings to be able to provide grid support services. Competitive markets should be established to drive efficient energy management outcomes through digitalisation. Artificial barriers that prevent demand management resources from participating in energy markets should be removed (Action 8.1). Certificate Schemes (Action 5.2, Action 8.3) are a proven mechanism with high benefit to cost ratios. Certificate schemes can be designed to achieve a target amount of digitally enabled DER from Grid Interactive Buildings, as the intended policy outcome (Action 8.4) Energy management incentive schemes will often need measurement and verification (M&V) to quantify and reward actions, in a performance-based way. Government-approved, digitally-automated M&V tools should be provided to industry - to streamline participation in markets and schemes (Action 5.3). While industry felt that digitalisation products and services can already compete without subsidies, industry adoption could be accelerated (in the short term) through direct incentives (Action 5.1, Action 2.3) and through mandated adoption in government buildings (Action 3.3) The NSW Peak Demand Reduction Scheme is an example of an innovative certificate scheme that aims to reduce *peak* electricity demand (rather than annual demand). By shifting the time when electricity is used, it can support more renewable energy generation in the system, and help households and businesses in NSW save around $1.2 billion between 2022 and 2040.
Workforce skills and capacity barriers	3.1 Maintain a centralised expert team to sup-port agencies 4.1 Engage the research sector in testing, analysis, knowledge sharing and developing tools and standards 7.1 Support digital training across the property sector. 7.2 Create incentive strategies for attracting IT talent into the property sector	Industry consistently identified workforce shortages and difficulty recruiting in areas associated with digitalisation. There is significant competition for talent with other sectors of the economy. Necessary skills in both consumer IT technologies and industrial OT technologies are less common. Government should develop an education and training agenda for improving digital skills in the property industry (Action 7.1, Action 7.2). Government can help improve focus on these skills by establishing digitalisation centres of excellence in both academia (Action 4.1) and government facilities management (Action 3.1). The UK Building Energy Management Systems Controls Engineer apprenticeship is an example of a training program designed to address the industry-wide shortage of BMS Controls Engineers. Commencing in 2021, it provides a comprehensive program of learning, delivered in partnership between the Building Controls Industry Association, and national training providers.

7. Conclusions

7.1 Summary of findings

The IEA-EBC Annex 81 'Data-Driven Smart Buildings' initiative explored the use of digitalisation, as an enabling tool for improving energy performance in non-residential buildings. Subtasks in the Annex focused on both (i) data analytics and artificial intelligence software applications (for improving energy productivity) and (ii) the digital (IT) infrastructure necessary to underpin these software applications.

Annex81 project partners collectively agreed that:

> *A Data-Driven Smart Building is a building that uses digitalisation technologies to dynamically optimise its operation, where optimisation objectives typically relate to site energy use, IEQ, and occupant experience.*
>
> *Ideally, it is sufficiently connected and integrated with markets and processes, that it can adaptively respond to externalities and changing conditions (e.g. weather, electricity prices, energy supply constraints, equipment maintenance, etc). Ideally, it has sufficient memory of past events, and ability to anticipate future impacts, that it can select an informed course of action for achieving higher-level objectives – reminiscent of human intelligence.*
>
> *To achieve this vision, a Data-Driven Smart Building utilises both live and historical data from relevant sensors, IoT equipment, mobile devices, and other sources, to provide situational awareness for informed decision-making. Achieving optimisation objectives will often benefit from advanced supervisory-level automation, driven by computational analysis (e.g. Machine Learning, AI, etc) applied to available data.*

Access to data is core to the success of AI applications in smart buildings. Data can be exchanged locally between devices on-premises. However, data accessibility (for potential users) is vastly improved by using cloud technology. The cloud enables a wider range of both on and off-premises data sources to be analysed together. The cloud also enables information to be efficiently distributed to relevant people via remote personal computers and mobile devices

7.1.1 Data and Digital Infrastructure

The generalised digital infrastructure, that Annex 81 considers suitable for implementing data-driven smart-building solutions, includes the following 'layers' in a software/hardware stack:

- **Device & Systems Layer**: In this layer, relevant data sources (from the equipment and sensors in the building) supply data to an on-premises data acquisition server via local wired or wireless protocols.
- **Network Layer**: In this layer, data is transmitted to a central cloud data platform (the data layer) via suitable communications gateway devices. Much of the cyber security requirements of smart buildings, are dealt with in the network layer.
- **Data Layer** (implemented as a data platform): In this layer (i) data is transposed and consolidated into common formats, (ii) data is stored in a structured queryable data base, and (iii) standardised interfaces are provided to make data accessible to software services (applications).
- **Application Layer**: This layer is hypothesized to be somewhat analogous to the App Store on a mobile device. The building owner would simply download their preferred services, and the software would self-configure to deliver the desired service.

The purpose of this software/hardware stack is to create a highly flexible digital infrastructure, that gives the building owner control over their digital resources, and access to 3rd party software services.

Core to the success of this digital infrastructure is interoperability. Interoperability issues relate to both (i) device-level communications (avoiding proprietary communication protocols) and (ii) the extent of informational/semantic context that is attached to the sources of data (ensuring sufficient metadata is available to give meaning to the data sources).

At a philosophical level, building owners should aspire to apply the FAIR data principles. That is, data is most useful when it is Findable, Accessible, Interoperable and Re-useable (FAIR).

Metadata – "data about data" – is used to organize the storage of collected data. It is also used by relevant software applications to automatically identify and retrieve data for processing. Utilising metadata is a key part of the FAIR data principles. Metadata schemas allow this to be done in a standardised way.

Metadata schemas are organisational structures for assigning metadata information to data sources. Metadata schemas standardise what information should be captured, and in what format. They provide a standardised structure for storing data that is independent of the choice of vendor or protocol, architecture and composition of building, or choice of data-driven consumers and processes.

While metadata schemas provide the general framework for organising information about a given building, the schema is not, in itself, the information about any given building. The actual metadata about a specific individual building is contained in a *metadata model*.

When deciding which metadata schema to adopt (for the data-layer), various characteristics and implementation factors should be considered. These include

- Structure of the metadata models that will be created
- Vocabulary, organization and completeness and strictness/rigor of the metadata schema
- Alignment with other metadata schemas
- Impact on smart building software architecture
- Required tooling / software support / expertise
- Model creation / bootstrapping / model maintenance

These considerations are discussed in Section 2.2.1.

Unfortunately, given the current low level of industry maturity, the process of creating a metadata model for a building can be challenging. It may not be clear how much modelling detail is required, to achieve the desired practical outcomes. Furthermore, tools for automating the process of validating a metadata model are in their infancy.

Data governance can also restrict the ability to share data with energy productivity analytics software. Licences may be required to access datasets owned by third parties (under copyright). Careful consideration should also be given to the possibility that data could be personal data. Six legal bases are provided under the European GDPR for sharing personal data. Even if there is a basis for sharing personal data, such sharing should be done with adequate protections. The Five Safes Framework can be used to identify protective measures for safeguarding personal data. The more sensitive the personal data, the stronger the protections will need to be.

The data-layer – which enshrines relevant interoperability and data governance considerations – is ultimately implemented as a data platform. In different contexts/applications the data platform could be called an IoT platform, an Energy Management Information System (EMIS) or Distributed Energy Resource Management System (DERMS).

Acquisition of a data platform is a significant strategic decision for the building owner. Key considerations for the building owner include (i) maintaining sovereignty over their data and (ii) avoiding vendor lock-in. There are various highly capable independent companies offering data platform services via a Platform-as-a-Service (PaaS) business model. The functionalities of some of these platforms, including some relevant government operated platforms, are reviewed in Section 2.4.

With access to a data platform, a building owner must decide what data to collect. It is generally acknowledged that, while there is no shortage of data that could be collected, it can be surprisingly hard to find the data that is needed.

By way of example, obtaining data for calculating key performance indicators (for benchmarking building performance) can be surprisingly difficult. Annex 81 conducted a review of building performance KPIs and their likely efficacy. KPIs were clustered against four target outcomes/ impact-areas; (i) Occupant-centric KPIs, (ii) Building Smart Technology KPIs, (iii) Building Energy Saving and Maintenance KPIs, and (iv) Energy Flexibility KPIs. The literature review identified 60 occupant-centric KPIs, 40 KPIs for transfer learning, 274 KPIs for building energy and maintenance, and 77 KPIs for building-to-grid interaction - resulting in a total of 451 KPIs.

A survey of 65 stakeholders found that KPIs that relate to occupant needs are typically prioritized, followed by KPIs relating to a building's energy efficiency and operation. Understandably, least concern was given to KPIs relating to electricity grid requirements.

A comprehensive evaluation was performed to ascertain the feasibility of computing various of these KPIs, across five case-study office buildings (four located in the Netherlands and one in Switzerland). The analysis used historical BMS data and focused particularly on occupant-centric and energy flexibility metrics. On average, only around one-quarter of the KPIs could be reliably calculated for the case study buildings with the available data.

- For occupant-centric KPIs: Some key considerations influencing the calculation of KPIs included (i) input data quality, (ii) unrepresentative spatial distribution of sensors, (iii) sampling frequency and temporal mismatches, and (iv) methods of aggregation/ averaging.
- For demand flexibility KPIs: Across 16 flexibility related datasets, there was a poor match between required data (for calculating KPIs) and available data.

Annex 81 participants interviewed leading industry practitioners, to further understand industry pain points and aspirations. Improving data quality and data management practices was seen as one of the key actions required to foster the spread of data-driven smart buildings.

Further details on these industry perspectives are presented in Section 3.2.

7.1.2 Energy Productivity Software Applications

Once suitable quality data is available and accessible, it is possible to deploy data-driven energy productivity software applications.

Some relevant software applications include (i) Trend Analysis using monthly energy bill data, (ii) Data Analytics using more fine-grained real-time energy (and sub) meter data collection to analyse equipment consumption, (iii) Equipment Fault Detection and Diagnosis (FDD) using sensor data, heating, ventilation, and air-conditioning (HVAC) equipment data and energy meter data, to identify problems with equipment operating patterns (iv) Advanced Supervisory Controls that can override static control set-points to take advantage of forecast knowledge (e.g. energy price forecast data and/or weather forecast data), and (v) Grid Integrated Control of Buildings, where buildings manage demand in response to requests (e.g. price signals) from energy utilities or market operators.

Annex 81 participants conducted research investigations and explored the state-of-the-art in relation to the fields of Equipment Fault Detection and Diagnosis (FDD), Advanced Supervisory Controls and Grid Integrated Control of Buildings

Fault Detection and Diagnosis (FDD) software is used to identify and diagnose faults (problems) in the systems and equipment operating in a building. FDD utilizes specialized algorithms to analyse data from sensors and equipment to identify and pinpoint the problems. This can be used by facilities managers and contractors to assist with maintenance and repair of installed equipment.

Traditional FDD uses logical if/then rules and decision trees. In contrast, data-driven FDD is software that is trained on ‘ground truth’ data using machine learning or multivariate statistical analysis methods. The data-driven algorithms learn what normal/good operation is and can then detect when something is deviating from this desired operation.

Across numerous buildings FDD software services have been shown to reduce energy consumption by around 9%, on average, with typical paybacks of two-years in portfolio implementations.

A literature review on data-driven FDD found that, while many data-driven methods have been used, the relative performance of the various algorithmic methods have not been adequately compared. The review also found that, in large buildings, the focus of FDD research has generally been on Air Handling Unit – Variable Air Volume (AHU-VAV) systems, fan coil units (FCU), chillers, and boilers. Among the papers reviewed, FDD methods were developed using either (i) laboratory experimental data (48%), (ii) simulation data (20%), or (iii) real building data (32%).

Some of the identified ongoing focus areas and challenges – required for further technical and market development of data-driven FDD, include:

- Real-Building Deployment
- Performance Evaluation, Benchmarking, and Fault Impact Analysis
- Scalability and Transferability
- Interpretability
- Cyber Security and Data Privacy
- User Experience

A persistent challenge for ongoing development of FDD is a lack of common datasets and algorithm test methods. These are essential to support benchmarking of new algorithms. A database of FDD datasets was created to address this gap. It includes data from 7 HVAC systems, with 257 fault cases (at different severity levels), and 8 billion data points.

Model Predictive Control (MPC) software uses a suitable mathematical model (digital twin) of the building and its systems, to provide forecasts of how the building will behave over the forecast future time horizon. This allows a supervisory ‘look-ahead’ controller to schedule equipment in advance, to optimise for comfort and energy savings. MPC is useful in virtually any situation where knowledge of the future allows for better decision-making.

Serale *et al.* (2018) conducted a review of the various implementations of MPC reported in the literature. They found that MPC implementations gave savings ranging from 0% to 40%.

A related alternative data-driven supervisory control approach is based on Reinforcement Learning (RL). The RL approach has the potential to avoid the need for a control-oriented model and the need for supervised learning of building performance. It does this by using a more trial-and-error based approach - that explores the state-space to find the control action (policy function) that maximises the given reward function. The difficulty for RL approaches is in obtaining sufficient data to explore the state-space and derive an appropriate control policy.

A persistent challenge for ongoing development of MPC and RL methods is a lack of common datasets and benchmarking tools for comparing the performance of alternative methods. Six high quality datasets, from real-world buildings, were created to address this gap. An innovative test environment (the Building Optimisation Testing (BOPTEST) framework) was used to conduct five benchmarking studies relating to alternative control algorithms. The BOPTEST framework has been developed to test control algorithms on a high-fidelity building emulator (rather than a real-world building). This avoids the practical issues of engaging with building owners and operators. It also creates a level playing field for comparing different algorithms.

All studies found that the MPC and RL controllers substantially out-performed the test building's conventional rule-based control strategies, in terms of providing better thermal comfort for occupants (lower Kelvin Hours outside of the target comfort thresholds) and reducing energy costs by around 20%. The best MPC solutions typically outperformed the best RL solutions.

These results are from a relatively small sample of studies. Further benchmarking research is required to build up the evidence base to cover more buildings, different approaches and different design choices for data-driven control.

Grid Integrated Control of Buildings software is used to control/modulate energy consumption, in order to provide demand flexibility services to local energy grids.

Annex 81 research focussed on (i) identifying definitions and KPIs for building energy flexibility assessment, and (ii) developing data-driven methods for calculating these KPIs. Research utilised metadata/ semantic principles to standardize the definitions and the computation of demand-flexibility related KPIs.

A literature review was conducted. 53% of the literature review studies considered flexibility at single-building level and 41% considered flexibility at building cluster level. Only 26% of the studies involved real measurements of flexibility, with 65% relying on numerical simulations. The review highlighted two challenges involved in quantifying energy flexibility, being (i) the lack of robust data-driven approaches for generating baseline load profiles (i.e. when demand response is not activated) and (ii) the lack of 'baseline-free KPIs' that can be computed without need for baseline or reference scenario inputs.

Some methods for generating a baseline include (i) Control group methods, (ii) Averaging methods (e.g. similar day look-up approach or 'X of Y'), (iii) Regression models, (iv) Shallow machine learning methods, (v) Deep machine learning methods, and (vi) Hybrid methods.

A persistent challenge to ongoing development of Grid Integrated Control of Buildings applications is a lack of datasets. 330 datasets were identified in the literature review as potentially of interest. Of these, only 16 were deemed adequate, with proper descriptions and open access availability.

Annex 81 participants developed an open-source Python toolbox, to help stakeholders calculate relevant KPIs and assess the demand response and energy flexibility available from buildings. The Python package leverages the EFOnt ontology to apply semantic principles, so that KPI definitions and computation is standardised.

7.1.3 Case Studies

A focus of Annex 81 research was to collect case studies of data-driven smart buildings. The aim of this work was to (i) gather evidence from real-world implementations, (ii) capture stakeholder perspectives and context, (iii) identify and summarise business models, (iv) highlight relevant applications and use-cases, and (v) document specific technologies and technology stacks.

A standardised two-page template was developed to enable case study information to be gathered consistently. Eighteen case studies were collected and made available through an online repository, representing a diverse range of building types, applications, and locations across thirteen countries.

Across all case studies, lessons learned revolved around four core themes: i) data quality and management, ii) technology specification and implementation, iii) stakeholder engagement, and iv) governance, compliance, and legal oversight.

Details of these lessons learnt are provided in Section 5.3.

7.1.4 Growing the Data-Driven Smart Buildings Industry

A core objective of the Annex 81 'Data-Driven Smart Buildings' initiative was to support industry growth and the adoption of digitalisation technology in buildings. Supporting this objective, Annex 81 work focussed on:

1. Stimulating innovation by running two data-driven artificial intelligence (AI) competitions, and
2. Consulting with industry, to identify barriers and to develop policy solutions that could overcome the identified barriers.

Crowd-sourced data science competitions are a powerful tool for developing innovative machine learning solutions. Competition platforms (e.g., Kaggle, AI Crowd and others) can be used to cost-effectively harness the collective intelligence of global participants. They also provide valuable learning opportunities for participants to sharpen their skills and to contribute to solving real-world challenges.

With funding support from ERA-Net Smart Energy Systems, the ADRENALIN (dAta-DRivEN smArt buiLdINgs) project was a consortium of 12 project partners (linked to Annex 81). The consortium organised two AI competitions.

1. The ADRENALIN Load Disaggregation Challenge required competitors to develop machine learning or statistical models that could take a building's site-level energy consumption meter data and disaggregate it - to quantify the energy consumption of the building's HVAC-related loads. Successful solutions could avoid the need for expensive submetering of HVAC equipment. The challenge attracted 47 participants and resulted in 13 valid submissions. 9 submissions successfully exceeded the minimum performance threshold set by the organisers.
2. The BOPTEST Smart Building HVAC Control Challenge required competitors to develop control algorithms that activate the flexibility potential of a building's HVAC system - based on variable cost signals, while not compromising indoor air quality. The winning entry would have the lowest weighted score (compared with the price ignorant baseline controller). The challenge attracted 22 participants and resulted in 5 valid submissions. 4 submissions successfully exceeded the minimum performance threshold set by the organisers.

Each winning team received a prize of 10,000 euros, distributed in two instalments: the first 5,000 euros awarded immediately upon announcement of the winners and the second 5,000 euros paid after a three-month knowledge transfer period with the sponsoring companies.

Various **barriers studies and solution roadmaps** have previously been conducted, with the aim of encouraging adoption of digitalisation (or digitalisation-based applications). Annex 81 participants conducted significant additional industry consultation research, to further understand industry pain-points and to identify policy actions that government could adopt, as a means of supporting industry growth.

Barriers identified, typically relate to (i) interoperability, (ii) privacy and cybersecurity, (iii) uncertain costs and benefits (poorly articulated business case), (iv) implementation complexity and (v) culture, trust and related stakeholder perception issues.

Based on stakeholder feedback, a number of solutions were identified. They were grouped under the following themes, and validated through industry consultation.

Theme 1: Provide Information – to reduce complexity and information asymmetry for buyers.

Theme 2: Establish 'digital ready' certification – to standardise solutions and recognise achievement

Theme 3: Lead by example – to provide a cohort of early adopters that catalyse the market.

Theme 4: Support researchers and innovators – to catalyse a wider range of product offerings, increase industry maturity, and provide independent validation of the benefits of digitalisation.

Theme 5: Incentivise EMIS technology – to improve the return on investment from the technology.

Theme 6: Reduce data sharing risk – to improve certainty and manage possible compliance issues.

Theme 7: Build workforce skills and capacity – to be able to deliver the services at scale.

Theme 8: Integrate buildings into the electricity system – to prioritise the clean energy transition.

A 'Policy Package' (plan on a page) was developed for driving adoption of digitalisation as a means of optimising energy use in buildings. Recommended actions to address the main barriers are:

Information and implementation complexity barriers:

Government should fund case-studies and pilots (Action 4.2, Action 5.1).

- Funding for case studies should be contingent on thorough knowledge-sharing using independent research bodies (Action 4.1).
  - Knowledge should be consolidated and shared through established professional channels, with media tailored to the needs of decision makers (Action 1.1).
  - Where possible, knowledge should be synthesised into relevant guides and standards that de-risk implementation (Action 1.2).
- Government can play a key role in creating information resources by investing in digitalisation technology across its own building portfolio (Action 3.2) and sharing the resulting knowledge.
  - Government should recruit a specialist centralised team with digitalisation expertise (Action 3.1), to support (de-risk) implementation in its own buildings, and to ensure that there is appropriate expert knowledge sharing.

Interoperability and data access barriers:

Government should publish guides with clear terminology to describe best practice digitalisation concepts (Action 1.2). Standardisation begins with the use of common language.

- These concepts can be further enshrined as standards and/or other requirements or specifications.
  - Industry adoption can then be driven by including these requirements in construction codes (Action 2.1), certification/rating schemes (Action 2.2), incentive schemes (Action 2.3) and/or mandatory equipment specifications (Action 8.2).
  - Relevant rating schemes, incentive schemes and/or markets will require certain data inputs. Regulatory support should be given, to ensure that these data inputs are available as standard (Action 6.1, Action 6.2), and access is not subject to or commercial and/or privacy constraints.
  - Government operated data platforms (linked to relevant government schemes) can play a key role in supporting efficient and scalable collection of standard data from industry (Action 6.3, Action 8.5).
- Government can play a key role in driving critical mass industry adoption of standards (and relevant voluntary schemes) by, for example, adopting digital ready clauses for its own buildings (e.g. through 'green-leases' (Action 3.3)).

Economic and first cost sensitivity barriers:

Government should support competitive markets that can drive efficient energy management outcomes through digitalisation. Artificial barriers that prevent demand management resources from participating in energy markets should be removed (Action 8.1).

- Certificate Schemes (Action 5.2, Action 8.3) are a proven policy mechanism with high benefit to cost ratios. Certificate schemes should be designed to achieve a target amount of digitally-enabled DER in Grid Interactive Buildings, as the intended policy outcome (Action 8.4)
  - Energy management incentive schemes will often need measurement and verification (M&V) to quantify and reward actions, in a performance-based way. Government-approved, digitally-automated M&V tools should be provided to industry - to streamline participation in markets and schemes (Action 5.3).
- While industry felt that digitalisation products and services can already compete without subsidies, industry adoption could be accelerated (in the short term) through direct incentives (Action 5.1, Action 2.3) and through mandated adoption in government buildings (Action 3.3).

Workforce skills and capacity barriers:

Government should develop an education and training agenda for improving digital skills in the property industry (Action 7.1, Action 7.2).

- Government can help improve focus on these skills by establishing digitalisation centres of excellence in both academia (Action 4.1) and government facilities management (Action 3.1).

7.2 IEA-EBC Annex 81 Resources

A number of resources have been developed or extended as part of the work of Annex 81 'Data-Driven Smart Buildings'. Readers interested in exploring these findings in more detail, or utilising the various research tools and data resources can go to the following online websites.

- Annex 81 'Subtask A report' on digital infrastructure for data-driven smart buildings: https://annex81.iea-ebc.org/Data/publications/IEA%20Annex%2081%20Subtask%20A%20Report.pdf
- Annex 81 'Subtask B report' on model predictive control
- Annex 81 'Subtask C report' on data-driven smart building software applications
- Report 'Data-Driven Smart Buildings State of the Art': https://annex81.iea-ebc.org/Data/publications/Annex%2081%20State-of-the-Art%20Report%20(final).pdf
- Report 'A survey of metadata schemas for Data-Driven Smart Buildings': https://annex81.iea-ebc.org/Data/publications/Survey%20of%20meta-data%20schemas%20(final)1.pdf
- Report 'A Data-Sharing Guideline for Buildings and HVAC Systems': https://annex81.iea-ebc.org/Data/publications/IEA%20Annex%2081%20Activity%20A1%20-%20A%20Data%20Sharing%20Guideline%20for%20Buildings%20and%20HVAC%20Systems%20(final)2.pdf
- Report 'Opportunities for Government Leadership on Data-Driven Smart Buildings': https://annex81.iea-ebc.org/Data/publications/Opportunities%20for%20Government%20Leadership%20on%20Data-Driven%20Smart%20Buildings.pdf
- Report ' A Guide on Data Platforms for Data-Driven Smart Buildings": https://annex81.iea-ebc.org/Data/publications/A%20Guide%20on%20Data%20Platforms%20for%20Data-Driven%20Smart%20Buildings%20(final)1.pdf
- Building Data Directory: https://buildingdatadirectory.org/
- FDD Dataset Repository: https://faultdetection.lbl.gov/
- MPC Dataset Repository: https://data.mendeley.com/datasets/xztfbtsgys/3
- Building to Grid Dataset Repository: https://aau-ef-kpi-web-app.build.aau.dk/
- BOPTEST Framework: https://boptest.net
- Energy-Flexibility-KPIs software tool: https://github.com/HichamJohra/energy_flexibility_kpis
- Data-Driven Smart Buildings Case-Study Repository: https://datasmartbuildings.org/

In addition to these deliverables, the Annex 81 website includes a catalogue of various articles produced by Annex 81 participants. The web page can be found at https://annex81.iea-ebc.org/articles

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