ANNEX 81

EBC
Energy in Building and Communities Programme

International Energy Agency

Data-Driven Smart Buildings: State-of-the-Art Review

Energy in Buildings and Communities Technology Collaboration Programme

September 2023

Technology Collaboration Programme by iea

ANNEX **81**

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Preface

The International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the Organisation for Economic Co-operation and Development (OECD) framework 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 coordinates international energy research and development (R&D) activities through a comprehensive Technology Collaboration Programmes (TCPs) portfolio. 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, considering a score 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, considering 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
Annex 81: Data-Driven Smart Buildings
Annex 82: Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems
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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

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

Executive Summary

The ongoing revolution in digital technologies and cyber-physical systems has the potential to reduce costs and overcome barriers to energy efficiency in building operation through dynamic control and operation of energy systems in buildings. These promising digital tools include:

- **Artificial intelligence and data analytics,** enabling more comprehensive energy performance assessment and predictive management of assets.
- The **Internet of Things (IoT),** providing access to more diverse, low-cost data on the status and activity of equipment and people in buildings.
- **Sharing economy platforms,** presenting new business models for connecting users and providers of energy-efficiency software services.

The IEA Annex 81 *Data-Driven Smart Buildings* was created in 2020 under the auspices of both Mission Innovation and the International Energy Agency's 'Energy in Buildings and Communities' TCP. Annex 81 is an international collaborative effort aiming to coordinate activities to better leverage ever-increasing data availability to improve the performance of buildings in terms of energy efficiency, environmental footprint, electricity grid participation and thermal comfort.

Annex 81 imagines a future world empowered by access to low-cost information-rich data from buildings, and where data-driven energy productivity solutions, such as model predictive control (MPC) and fault detection and diagnosis (FDD), can be deployed, at a large scale, on real-time data-exchange platforms with high levels of interoperability. Annex 81 will support the development of innovative new software solutions by collating high-quality datasets, benchmarking solutions in standardised virtual test environments, and hosting AI competitions.

This report, a deliverable of Annex 81, reviews the state-of-the-art related to Data-Driven Smart Buildings research and technologies. It explores issues relating to IT infrastructure and data management procedures necessary for streamlining the deployment of data-driven software solutions. It also examines recent developments in data-driven approaches for optimising building energy performance, including fault detection and diagnosis, advanced control strategies and the interaction between buildings and the electric grid. The report covers the following aspects of the utilisation of data in building operation:

- **What is a data-driven smart building?** Chapter 1 discusses the features of data-driven smart buildings, the focus of Annex 81. Some desirable features attributed to smart buildings were identified by participants of the Annex, including "adaptability", "flexibility", and "forward-thinking". Achieving the attributes of a "data-driven" smart building, requires considering the real-time interaction between software and data (exchanging between sensors and devices in the building). Data must be findable, accessible, interoperable and reusable (FAIR) to support automated discovery and analysis by machines. This suggests two-way communication through "data pipes" between authorised users of data, supported by a systematic approach to organising the data, consent to data utilisation, and cybersecurity. Advanced analytics can then deliver insights and decision support through awareness of historical performance and ability to forecast future performance. While not an essential feature, a smart building is typically cloud-connected. Chapter 1 concludes with an Annex81 definition of a smart building.

- **Data platforms and information management.** Chapters 2 and 3 discuss a key challenge for "data-driven" smart buildings: how to organise the building operation data to be easily retrievable, contain contextual information, and be securely stored for diverse applications. Chapter 2 focuses on "platforms", exploring the different levels of data storage quality and the data management features of a digital platform that make it useful for sharing and processing data. These features include 1) *data governance*, i.e., who can access data, how long it can be stored and so on, 2) *metadata* for easy location of data on the platform 3) *procedures for data cleaning and sorting*, to improve data quality and provenance and 4) *plans* on how to use data. Open software tooling and data standards are recommended to enable third parties to utilise data on the platform.

Chapter 3 addresses the formidable challenge of standardising the use and application of metadata ("data about data"). In buildings containing thousands of data points, deciphering cryptic variable names and understanding their contextual implication is one of the barriers to the mainstream adoption of data-driven solutions. While some outstanding efforts in this direction have been made (Haystack, Brick, ASHRAE 223P, etc.), it remains one of the challenges ahead. Finally, Chapter 3 discusses where and how meta-data can be sourced and ingested into data platforms, including from building automation systems (BAS), building information models (BIM) and inference from various data-mining techniques applied to the data-source.

- **Data-driven advanced controls**. Chapters 4 and 5 address model-based predictive control and other data-driven control strategies, one of the areas in which data-driven solutions can be profoundly transformative. Although research studies and demonstration projects consistently confirm the potential of data-driven advanced control, this approach is far from being a mainstream practice. Apart from the abovementioned challenges of keeping and accessing tabulated data, the gap between the leading edge of research and the control industry is partly explained by the challenge of creating appropriate control models (discussed in Chapter 4), which range from carefully constructed "white-box" models based on physical principles to the purely "black-box" based on large datasets of inputs, including a vast continuum of "grey-box" models. Grey-box models represent an "in-between" approach combining physical insight and data analytics. Chapter 5 scrutinises, in depth, the scientific and mathematical aspects of formulating optimal control problems using a data-driven model, incorporating forecast uncertainty as a consideration. Chapter 5 presents in detail a demonstration project showcasing the mathematical formulation and the real-life application of predictive control. Chapter 5 proposes a hierarchical approach for the control of smart grids based on the flexibility function as a unifying minimum interoperability mechanism (MIM) that couples control strategies at different levels. With this approach, stochasticity has a less significant impact in larger systems; but as the analysis focuses on smaller scales, uncertainty becomes more important.

- **Fault detection and diagnosis (FDD)**. Chapter 6 discusses this application, which is among the most mature of the data-driven technologies. The vast literature in this field includes applications for several types of HVAC equipment (the most common ones being air-handling units and chillers), a vast array of metrics to assess the performance of systems based on collected data, fault prognosis algorithms to predict the likely cause of an issue, diagnosis algorithms to identify potential causes, etc. The chapter concludes by discussing strategies to generalise FDD algorithms to make their adoption easier and more widely accepted. Such strategies include using "hybrid" approaches that extend the range of data from which a reliable conclusion can be extracted, incorporating the concept of "transfer learning", a branch of machine learning whereby a model created for a given situation can be applied for a new (albeit similar) system. Just as in the case of predictive control, FDD will considerably benefit from the widespread adoption of the abovementioned metadata standards.

- **Building to grid interaction (B2G)**. One of the areas in which data-driven applications will have a significant impact is the improvement of the interaction between buildings and energy networks via increased data accessibility (energy metering, pricing signals, occupancy, weather) and an enhanced capacity to share this data. In future energy systems, buildings will not be considered in isolation but as part of a complex energy ecosystem in which electric energy is dynamically traded between a centralised source (the grid) and buildings. Commercial and residential buildings have traditionally worked as passive entities and consumers; instead, they can increasingly provide generation and storage capacity, gradually transitioning into "prosumers". High-resolution data of exported-imported electric power can be used to accurately model this interaction and conceptualise business models to benefit both buildings and the grid. At the core of B2G is the concept of flexibility, i.e., the ability of the building to adjust its power demand on requests from the grid.

Chapter 7 discusses the two main approaches for demand response: direct control and indirect (or incentive-based control). In direct control, the building demand is adjusted by directly altering the operation of the equipment while targeting an aggregated load within a set of requirements for functionality and comfort. Direct control is often organized around a “flexibility market”, in which “negotiation” occurs (market offer/bidding) between the energy suppliers and the buyers before the energy service is required. At a small scale, e.g. between individual commercial buildings, this can take place via peer-to-peer (P2P) energy trading. In indirect control, a “penalty” or a pricing signal is used to motivate the building operators (or the control system) to correct the building demand.

An interesting example of a data-driven B2G framework is the *Smart Energy Operating System* (SEOS) in Denmark, combining direct and indirect control features depending on the scale. The SEOS relies on minimum interoperability mechanisms (MIMs), i.e. the minimum information blocks that enable the interaction between systems.

Chapter 7 also presents a set of demonstration projects and real-life B2G applications. While the technology is relatively mature for deployment, its widespread implementation confronts a set of hurdles: regulatory barriers (e.g., inadequate legislation framework), technological challenges (e.g., the cost of deploying metering and communication equipment, inadequate “legacy” building automation systems, lack of standardisation in communication protocols). Finally, appropriate economic barriers remain an issue, as the benefits that deploying B2G technologies will bring to energy service companies, aggregators and homeowners are relatively unclear.

- **Collection of case studies**. Annex 81 has engaged in gathering information from case studies of data-driven smart buildings worldwide. A thorough survey is used to obtain contextual information about the projects (type of building, climate, location), the business models in place for a data-driven control approach, the stakeholders involved, etc. The compilation of the case studies has provided interesting lessons. For example, there tends to be a limited effort in documenting metadata, a fact which limits the datasets’ applicability. Issues related to the accuracy of the data present challenges for creating accurate simulation models. However, collected data provided evidence of the impact of changes in control strategies. For instance, the adjustment of ventilation rates in response to the Covid-19 pandemic had a measurable impact on energy use patterns.

  The lack of documentation at all stages of a project is another fact that limits the serviceability of the data. More information is needed about the early design stages, how the original plans were later revised (“as built”), and the changes that took place during the commissioning process.

  The impact on occupant comfort was a significant factor. Occupants are often reluctant to accept a fully automated system that prevents overriding its settings. Nevertheless, occupants can accept setpoint variations for energy management if their impact on thermal comfort is not noticed. While predictive control strategies have provided only marginal comfort improvements, they do achieve the objective of energy savings.

  There is also room for improvement in the legal framework related to data-driven technologies. For example, regulations are required regarding the results of simulations and their impact on the description of how the building operates, criteria for the definition of energy-saving targets and privacy issues related to collecting data from the occupants to enhance building operation.

  Finally, as Chapter 8 concludes, scaling the adoption of data-driven smart buildings requires articulated value propositions, information on best practices and technical pathways to achieve real-world implementations, engagement from the occupants and building operators, and additional training in an often-conservative industry. Finally, privacy and cybersecurity must be addressed to increase confidence in data-driven technologies.

Table of Contents

Abbreviations

Abbreviations	Meaning
AHU	Air handling unit
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
API	Application programming interface
AUC	Area under the curve
AI	Artificial intelligence
ANN	Artificial neural network
AE	Autoencoders
ARMA	Autogressive moving average model
AR	Autoregressive model
ARX	Autoregressive model with exogenous input
ARMAX	Autoregressive moving average with exogenous input model
BN	Bayesian network
BACnet	Building automation and control networks
BAS	Building automation system
BIM	Building information model
BMS	Building management system
BOPTEST	Building operations testing (software tool)
BPS	Building performance simulation
B2G	Building to grid
CSIRO	Commonwealth Scientific and Industrial Research Organisation (Australia)
CNN	Convolutional neural network
CD	Correct diagnosis
CDR	Correct diagnosis rate
CYDRES	Cyber Defense and Resilient System
DB	Database
DT	Decision trees
DR	Demand response
DSO	Distribution system operator
DH, DHN	District heating network
EMPC	Economic model predictive control
EV	Electric vehicles
EBC	Energy in Buildings and Communities Program
ESCO	Energy service company
FN	False negative
FNR	False negative rate
FP	False positive

FCU	Fan coil units
FDD	Fault detection and diagnosis
FAIR	Findable, Accessible, Interoperable, Reusable
FF	Flexibility function
FMU	Functional Mock-Up interface
GDPR	General data protection regulation
GAN	Generative adversarial network
GB	Gradient boosting model
GHG	Greenhouse gas
GEB	Grid-interactive efficient buildings
HP	Heat pump
HVAC	Heating, ventilation and air conditioning
HEMS	Home energy management system
HMIS	Home management information system
HTTP	Hypertext transfer protocol
IAQ	Indoor air quality
IEQ	Indoor environment quality
IFC	Industry Foundation Classes
IGFF	Information greedy feature filter
IEA	International Energy Agency
IoT	Internet of Things
KPI	Key performance indicator
LBNL	Lawrence Berkeley National Laboratory
LIME	Local interpretable model-agnostic explanations
MIM	Minimum interoperability mechanisms
MD	Misdiagnosis
MDR	Misdiagnosis rate
MPC	Model predictive control
NREL	National Renewable Energy Laboratory
NN	Neural network
NDR	No detection rate
NDgR	No diagnosis rate
OPC-UA	Open platform communication-Unified architecture
P2P	Peer to peer
PV	Photovoltaic
PCA	Principal component analysis
RF	Random forest
ROC	Receiver operator characteristic
RNN	Recurrent neural networks
RL	Reinforcement learning
RESTful	Representational state transfer

R&D	Research and development
RISE	Research Institutes of Sweden
RC	Resistive-capacitive networks
RDF	Resource description framework
RBM	Restricted Boltzmann machines
RTU	Roof top unit
SSN-SOSA	Semantic sensor network-Sensor, observation, sample and actuator
SAREF	Smart applications reference ontology
SE-OS	Smart energy operating system
SDE	Stochastic differential equations
SQL	Structured query language
SVM	Support vector machine
SVR	Support vector regression
SOP	Symptom occurrence probability
TRL	Technology readiness level
TES	Thermal energy storage
TSO	Transmission system operator
TN	True negative
TNR	True negative rate
TP	True positive
TPR	True positive rate
URI	Uniform resource identifier
URL	Uniform resource locator ("address")
URN	Uniform resource number
VAV	Variable air volume
VRF	Variable refrigerant flow
VBIS	Virtual building information system
OWL	Web Ontology Language

1 Introduction

- Smart Building Features
- Definition of Smart Building
- The role of IEA Annex 81

1.1. IEA EBC Annex 81

The IEA EBC Annex 81: *Data-Driven Smart Buildings* was created in 2020 under the auspices of the Mission Innovation Initiative. Annex 81 is an international framework to coordinate efforts to better leverage the ever-increasing data availability to improve the performance of buildings in terms of energy efficiency, environmental footprint and thermal comfort.

1.2 What is a Smart Building?

“Smart Buildings” is a frequently used but poorly defined term. So, how can we define it? In the following pages, we will discuss some of the definitions presented by different research teams and organizations, as well as some of the critical features that underscore the “smartness” of a building. We will focus specifically on the requirements of a *data-driven* smart building, a specific subset of smart buildings in which data utilization is at its core.

1.2.1. Earlier Definitions

Many definitions are provided for a Smart Building in the literature. Some examples are provided below. While not comprehensive, or necessarily authoritative, they highlight some interesting perspectives for discussion purposes.

Sinopoli (2010) proposes a definition based on **the availability of technologies in the building**: "*a smart building involves the installation and use of advanced and integrated building technology systems. These systems include building automation, life safety, telecommunications, user systems, and facility management systems. Smart buildings recognize and reflect the technological advancements and convergence of building systems, the common elements of the systems and the additional functionality that integrated systems provide. Smart buildings provide actionable information about a building or space within a building to allow the building owner or occupant to manage the building or space. Smart buildings provide the most cost-effective approach to the design and the deployment of building technology systems*."

Zhou and Yang (2018) propose a definition that underscores the interaction **between systems and data gathering from equipment**. They refer to a Smart Building as a “*type of building with reasonable investment, efficient energy management, and comfortable and convenient environment, designed by considering the optimized relationship among structure, system, service, and management […] it has intelligent control systems and smart and interconnected devices beyond the traditional building structure and function’ and that IoT ‘is one of the major technologies of smart buildings … supported by web-enabled hardware, automation devices, and sensor networks.”* Zhou and Yang suggest that “*hybrid electrical energy storage (HEES)* systems will be widely used in smart buildings that are equipped with some renewable sources of power generation such as solar panels mounted on the rooftop*", and "*smart buildings also provide a better air ventilation system to improve the environmental quality [where] the temperature, humidity, and ventilation rates are controlled by the intelligent devices.*"

1.2.2. Attributes and Functionalities

Figure 1-1, created by the Buildings Performance Institute Europe, depicts a "smart built environment".

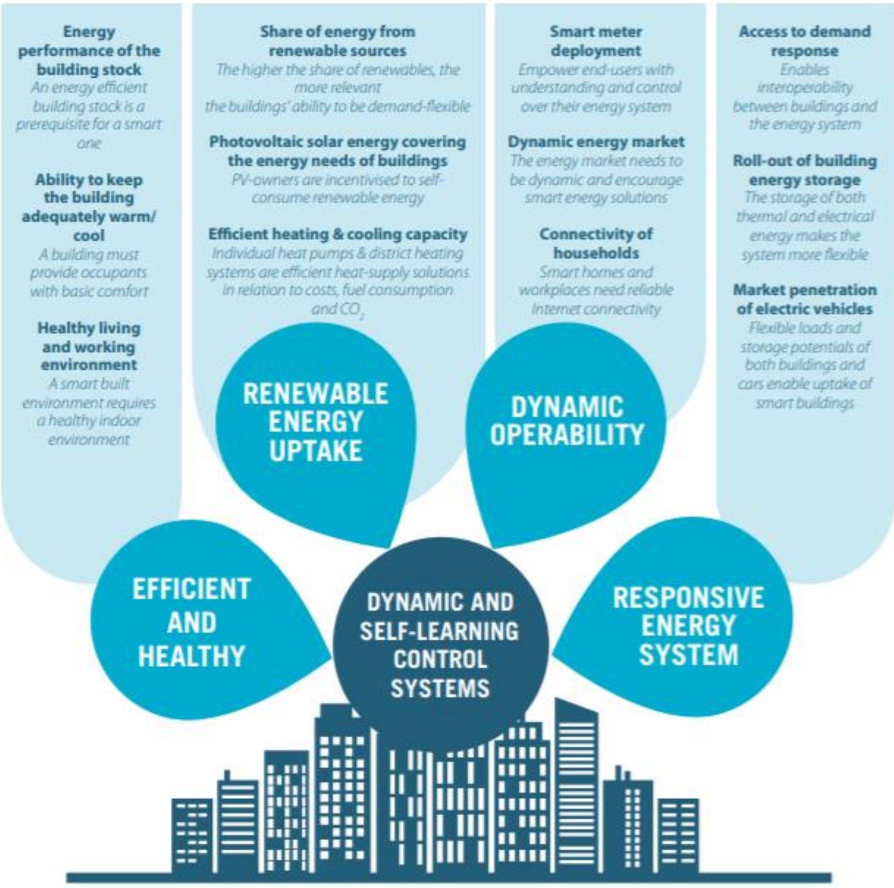

Figure 1-1. Characteristics of a Smart Building. *Source*: Buildings Performance Institute Europe (BPIE), DeGroote et al. (2017)

These features combine aspects of "Industry 4.0 style" advanced automation with a range of other considerations, such as:

(i) improved design and hardware selection
(ii) superior performance through integrated/systems thinking and
(iii) cost-effectiveness.

This diversity of thought is also reflected in the variety of certification schemes aiming to identify those buildings which can be considered 'smart' (see subsection below).

Annex 81 conducted an online *Mentimeter* survey where participants were asked to suggest the key attributes of a smart building. The results are illustrated in Figure 1-2. This word cloud hints at a vision of a smart building as one that has understated automation, working in the background, to anticipate and responsively (i) service the needs of occupants and (ii) optimise the operation of equipment parts as an integrated system. This outcomes-based vision aligns well with the concepts of 'digitalisation' and Industry 4.0.

Figure 1-2. Attributes that characterise a Smart Building. *Source*: IEA EBC Annex 81 Mentimeter Survey.

Working in small groups of five to six persons, IEA Annex 81 participants further explored the technology features that underpin a Smart Building. The discussions identified key Smart Building technology attributes and functionalities, being:

1. **Building-services hardware and software interact in near real-time to deliver value.** This requires two-way data communication between sensors, devices, and servers. It further anticipates that the result of applying 'smart' analytics will lead to automated machine-to-machine dispatch of requests for action (e.g., adjustments to control settings) to deliver a value-adding result (rather than just providing information for subsequent ad-hoc human consideration). Furthermore, the central processor is assumed to be continuously learning from the streaming of sensor data and from ad-hoc human intervention, giving it predictive capability for the relevant objective functions of interest (e.g., energy minimisation, equipment performance, etc.).

2. **Building infrastructure has "data-pipes", and related processes and tools to ensure data quality**. It is understood that 'garbage in leads to garbage out'. Consequently, there is a strong emphasis on the need for technical functionality that can deliver high-quality data. Data quality relates not just to data cleaning and gap filling but to a range of other factors, including:

   a) *Labelling and context*

   - **Data richness**: A simple unlabelled data stream is generally of limited value. Additional information (metadata) on the source of the data, the physical meaning of the data, the units of measure, how the source of the data relates to other objects in its ecosystem, etc. —all add context that can be used to infer causation of events and achieve desired outcomes. By way of example, address-matching is often a means for linking records, utilising analytics to discover new correlations, and enabling administrative processes. In many Industry 4.0 use cases, time stamping is also required to ensure that diverse data sets can be validly compared.
   - **Ground truth**: Machine learning algorithms will often 'train' using 'ground-truth' data where the target event or condition is known to occur. After training, the algorithm is then able to detect the

event/condition from other confounding factors. In this way, access to ground truth meta-data can greatly improve the value of data.

- **Provenance:** The validity of data can be compromised in a range of ways. For example, sensors can go offline due to connectivity issues, they can fail to update (leading to a static signal), technicians can alter some hardware or software configuration (and possibly fail to log changes), etc. A secure digital identity is required for assets to enable them to be coordinated. Some form of data health, traceability and data provenance tools could help ensure that decisions are made based on correctly identified and operational information.

b. Structure and discoverability

Rich data sources, which incorporate relevant metadata (as above), can be stored in a suitably structured database. Such a database can then be queried by machines based on logical relationships. Cloud-hosted Industry 4.0 processes (software applications) can then discover and orchestrate the operation of devices. The extent to which database structures can be aligned with industry-wide open data schemas will influence the efficacy of industry collaboration. Web Ontology Language (OWL) data schemas further support seamless integration with diverse cloud-based data sources, supporting the potential for innovative Industry 4.0 use-case applications and “PropTech” (entrepreneurial IT-based property technology products) business opportunities. While not directly developed for Industry 4.0, the so-called FAIR (Findable, Accessible, Interoperable, Reusable) data principles (Wilkinson et al., 2016) can help inform data management approaches for streamlining data exchange and avoiding expensive bespoke solutions.

c. Consent, privacy and cyber-security

Just because data is available does not mean it can be ethically used. It is essential to note that relevant Industry 4.0 use-cases may involve interaction with occupants and perhaps an inadvertent collection of personal data of the occupants. While data ethics and data security issues are discussed separately, it is noted here that a Smart Buildings IoT platform should provide technical functionality to overcome many of these concerns (including streamlined consent processes).

1.3 Data-Driven Smart Building Definition

In the light of the preceding discussion, we participants of Annex 81 have proposed the following definition:

> *Data-Driven Smart Building: A Data-Driven Smart Building is a building that uses digitalization technologies to dynamically optimize site energy use, indoor environment quality (IEQ) and occupant experience.*
>
> *Ideally, it is sufficiently connected and integrated with external markets and processes, that it can adaptively respond to changing conditions (e.g. provide flexible demand services to electricity markets). Ideally, it is sufficiently aware of future impacts, such 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 will utilise live and historical data from relevant sensors, IoT equipment, mobile devices, and other data sources to provide situational awareness for informed decision-making. Realizing the desired physical optimization objectives, will often then require advanced automation, driven by supervisory-level analysis of input data.*

> *Sourcing, managing, analysing and dispatching input/output data - from measurement through to equipment automation and control - can be streamlined with emerging digital technologies, protocols and methods. To this end, the functions and technical attributes that underpin the infrastructure of a Data-Driven Smart Building may include some combination of (a) continuous data quality validation and assurance; (b) open-standard communication protocols that provide interoperability between devices; (c) an open-standard data structure that facilitates storage and use, for different use-case applications and by different software vendors; (d) AI/machine-learning analytics that informs maintenance and/or control processes in the building; and (e) automated dispatch of commands to orchestrate equipment operation at supervisory level.*
>
> *Open standards (communication protocols, data schemas, interfaces etc) should be used, where possible, to avoid vendor lock-in and maximize interoperability.*
>
> *While many digitalization functions can and will be performed onsite (at the 'edge'), new applications and business models can also take advantage of cloud-based data platforms. Data platforms provide a Smart Building with means for exchanging data with a wider variety of sources and users (cloud-hosted databases, IoT, mobile devices etc) and a means for utilizing powerful software tools and workforce skills available from the IT industry.*

This definition begins with high level principles of what a data-driven smart building is, its purpose, and the characteristics that identify a building as smart. It finishes with a more detailed discussion of digital technologies and concepts that combine to provide best practice smart building capability. In this way, it aims to provide the reader with a more explanatory definition expanding on that of Verbeke et al (2020). It is hoped that this definition will provide the reader with some extra concepts and language to begin a conversation about implementing data-driven smart building technology.

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2. Open Data Platforms

- Role of Data Platforms
- Existing Data Platforms
- Identify components related to environmental and energy infrastructure

2.0 Role of Data Platforms

The built environment field is plagued by information silos and a lack of standardization that affects the information flow. Current practices for building automation and management that control heating, ventilation and air conditioning (HVAC), lighting, access control and security traditionally act as silos which are operated independently and are provided as proprietary systems by multiple vendors (McGibney et al., 2016)

We know that equipment data from building automation systems and data from IoT (Internet of Thing) sensors are increasingly being uploaded to the cloud. With this, there is an opportunity to drive modern data analytics and machine learning 'Applications', that can reduce energy consumption and enhance productivity. However, we also know that there are still challenges, as companies are still struggling to consolidate data from multiple disconnected systems and service providers. Also, when onboarding, building innovators often must invest significant effort in getting access to sites, creating custom interfaces to equipment, decoding point labels, etc., before they can add any value to the data through new analytics applications. Therefore, there is a need for both useful platforms and harmonization within the sector.

We see that today's existing closed and proprietary system limits the possibility and further development of innovative solutions for the management of buildings. This is because new system innovations in the form of data-driven services are difficult to implement alongside existing systems. Often it is necessary to make an intrusive impact on the existing system or let the existing system supplier upgrade the platform. With platforms that are more open and open APIs, each property owner would be able to let different actors use the property's data for innovative control without being hindered by the existing owner directives, Part of this movement is already happening today as the Internet of Things breaks through and places data flows and digital services as a parallel infrastructure – but this is currently happening at the cost of double measuring and control infrastructures in many buildings. This would be possible to prevent if a more open infrastructure would be used.

2.0.1 Digital Building Automation

In support of efforts towards achieving targets regarding the indoor environment, energy efficiency, CO_2-emissions, profitability, etc., we have a growing number of digital tools at our hands at different stages.

The illustration below (Figure 2-1) shows different maturity levels with regards to digital building automation. At the most basic level, there might only be local control. Moving up the ladder, we have connected control and different levels of SCADA systems and beyond.

- At the first level, **local control**, the property is managed primarily manually, and control is done locally.
- At the second level, **connected control**, the field units are connected via a control system.

- At the third level, **super-ordinate control**, there is a SCADA system in place, which enables different systems to communicate with each other; this is where many commercial properties are today. However, even if there is a SCADA system, there is often still optimization left to be done.
- We are now beginning to see a shift towards the fourth step, where we have advanced SCADA systems, i.e., **advanced super-ordinate control systems**, which have advanced functions in the user interface, and where machine learning and artificial intelligence are used to optimize the operation automatically.

The movement up this ladder of maturity can be done either through proprietary systems or open systems or a combination of both.

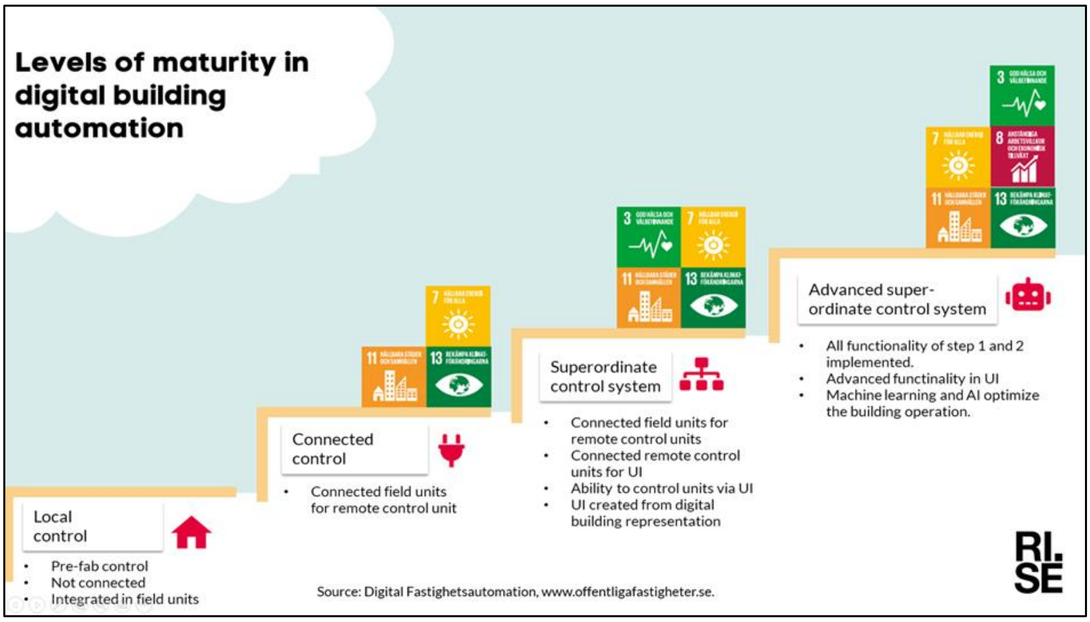

Figure 2-1. Levels of maturity in building automation.
Source: Digital Fastighetsautomation, www.offentligafastigheter.se.

2.0.2 Stages of Data Deployment

Data needs to be organized in an efficient and sufficiently accessible manner. Tim Berners-Lee, the inventor of the World Wide Web and Linked Data initiator, has suggested a 5-star deployment scheme for Open Data (Figure 2-2). This structure is quite relevant for Annex81 and future projects on data-driven smart buildings.

- At the first level, **data is available on the Web** (regardless of format, as long as it is under an open license). This means that everyone can access data and then save, download, modify, and share it with anyone. According to the Berners-Lee framework, to get one star, you must make your material available on the Web, in any format (e.g., a PDF). However, it must be under an open license; otherwise, others cannot use it.
- At the second level, **data is available as structured data** (like an Excel file instead of an image of a table). This allows for processing with some proprietary software to aggregate, visualize, manipulate and export the data to another structured format.
- At the third level, **data is available in a non-proprietary, open format**. It is exactly as the second level, but without the need of proprietary software (e.g., CSV instead of Excel).
- At the fourth level, things start to get interesting, **as data is *on* the Web**. Data is linked to a URI (Uniform Resource Identifier), which makes it possible to "locate" it. A URI consists of a URN (Uniform Resource Number, the "name" of the object) and an URL (Uniform Resource Locator, the

“address” of the object). This makes it possible to bookmark data, link from any place on the Web or locally, reuse parts of data or even reuse existing tools and libraries.

- At the fifth level, **data is linked with other data**. By doing so, data becomes discoverable, increasing its value thanks to the network effect, as the value of data increases with the number of links connected to it. Both the consumer and the publisher benefit from the increased connection.

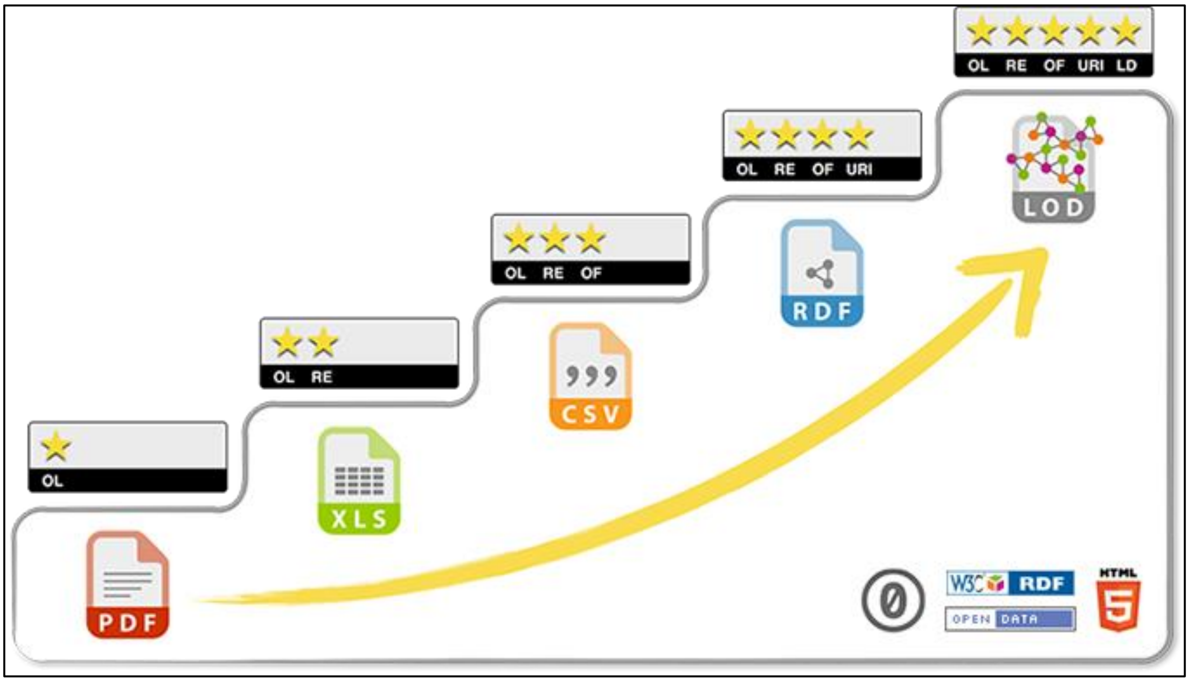

Figure 2-2. Data deployment schemes. *Source: https://5stardata.info/en/*.

2.0.3 Handling the Data: Data Lake vs Data Swamp

Once the data has become available and we want to use it to run our smart control strategies, we need efficient ways to handle all the data. The illustration below (Figure 2-3) summarizes the qualities of a “Data Swamp”, i.e., with broken or no metadata management versus a “Data Lake”, with metadata management in place. Naturally, a data lake (structured database) is preferable to a data swamp. A useful data sharing platform needs sufficient metadata, data governance and data cleaning.

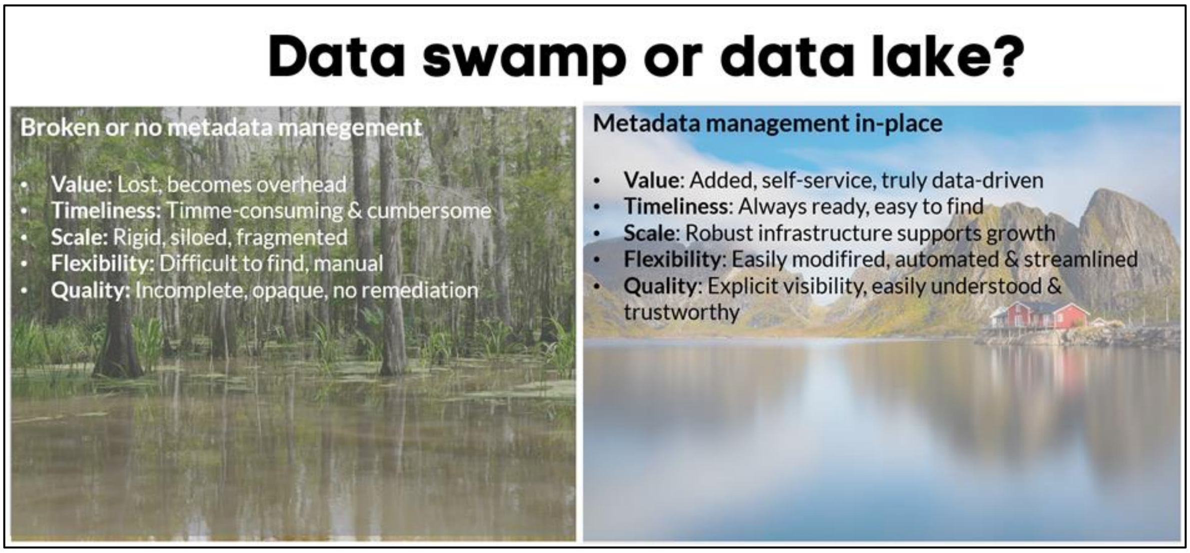

Figure 2-3. Data swamp vs data lake. Metadata management.

A **data lake** is a centralized repository (the lake itself, i.e., the water reservoir) that collects a great amount of both structured and unstructured data from different sources (the incoming flow), which can be later analyzed (the outcoming flow). Data is stored in its original format, from multiple sources, which can be as diverse as data from IoT devices, mobile applications, social media, email conversations, allowing for real-time data collection. The idea is to store the data "as is", without applying a rigid structure to it but containing informative tags, thus saving time and resources. It is akin to gathering a lot of different (but clearly labelled) objects in an attic without knowing exactly what we will do with them as we get them. A data lake is cheaper than structured storage since data does not need to be in a particular format when we store it.

The beauty of a data lake is that it allows different users to access their data of choice, the same way people will choose to do different activities at a lake. A business analyst, a data scientist or a data developer can access the lake with her choice of analytic tools and frameworks. This allows every user to pursue his particular goal without being bound to using a specific data analysis method or software. A data lake can be, in its own right, a “data sandbox” for discovery and exploration, where the user with the right idea and the right tools can derive useful insights and find the treasure at the bottom of the lake. A data lake must provide the following features: 1) *data governance*, i.e., who can access data, how long it can be stored and so on, 2) *metadata* for easy location of data within the lake 3) *procedures for data cleaning and sorting*, to improve data quality and provenance and 4) *plans* on how to use data.

To run different types of analytics —from visualizations and dashboards up to big data processing, real-time analytics, and machine learning— defined mechanisms to catalogue and secure data in the lake must be in place so that data can be not only found but also trusted. Without regulating the “instreams and outstreams” and periodical dredging of the bottom, outdated and unnecessary data accumulates, and the lake turns into a swamp.

A data swamp is not suitable for data analytics, mainly for two reasons: 1) a lack of metadata makes finding specific data very hard or impossible, 2) a lack of organization and governance, resulting in unreliable and useless data being dumped into the swamp. In short, it is almost impossible to generate useful insights when analysing the data from a swamp.

While a data lake is cheaper and easier to use than a structured database, it is not completely unregulated: it must guarantee that data is always useful and relevant by using metadata and a set of rules and procedures for data access and storage.

2.1 Towards *Open* Data Platforms

An important attribute of platforms for data-driven smart buildings is that they are *open*, meaning they are based on published and documented standards and protocols. Importantly, “open data platforms” do not need to be “open source”; as long as interactions with the platform do not depend upon proprietary, licensed, obscured or otherwise “closed” technologies and standards, the platform can be considered “open” because it allows for third-party clients and applications. Open platforms allow developers, users, and other platform consumers to interact with, download, and analyze data using the language or toolchain of their choice.

Open platforms are important because they enable a collection of platforms and technologies to compete evenly in the same ecosystem without consumers of the platform paying the price of vendor lock-in or having to choose an ecosystem in which to invest. Open interfaces serve as the point of interoperation between platform providers and platform consumers. As long as the interface contract is fulfilled, platform developers can innovate their offerings to provide better qualities of service or advanced features. Consumers of the platform do not have to be concerned with the implementation details because of the abstraction offered by the open interface. Additionally, basing interfaces on open, publicly available, and documented standards means that consumers of the interface do not bear the risk of platform deprecation or backwards incompatibility. Once a critical mass is achieved in a software ecosystem, consumers can be more willing to consider the adoption of data-driven buildings, because there are multiple providers with mutually compatible software.

At the time of writing, few open platforms and protocols have emerged for data-driven smart buildings. Most early adopters choose to expose the underlying databases directly to their applications. For building telemetry, this often means using standard SQL to interact with relational databases like TimescaleDB, or writing Flux queries to interact with a timeseries database like InfluxDB. Chapter 3 below describes the use of open metadata standards for describing buildings and their data; this metadata can often be accessed using the standard SPARQL query language (for RDF-based metadata). Platform providers like SkySpark and Data Clearing House create their own HTTP API for interacting with metadata and data together.

2.2 Conclusion

Data platforms serve up the data generated by underlying cyber-physical systems (such as those typified by the Internet of Things) to facilitate access by downstream applications. Due to the complexity of the underlying cyber-physical systems, it is necessary to provide descriptive *metadata* which can be processed or queried by consumers of the data platform. This metadata provides essential contextual information which permits interpretation of the data. In the following chapter, we describe the essential properties and key characteristics of managing metadata and data together for data-driven smart buildings.

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3. Data Information Management

- Why data and metadata management are crucial to the operation of data-driven smart buildings at scale
- Data and metadata models that have emerged to address these issues
- Challenges in creating, curating and managing data and metadata for buildings
- Future opportunities

As the availability, heterogeneity and scale of data in buildings increases, so does the need to effectively manage that data to maximize its utility to stakeholders. Data management is the practice of ingesting, organizing, storing and accessing information. We expand the definition of data management for the building domain to include management of *metadata* — so-called “data about data” — which allows relevant data to be easily identified and extracted by data consumers. In this section, we provide an overview of the primary components of data and metadata management solutions comprising how to represent and organize data and metadata, how to produce and maintain data and metadata, how to store and access data and metadata, and finally, how to validate and process data and metadata. These techniques, technologies and solutions should be incorporated into data platforms such as those covered in Chapter 2.

Managing data for buildings must grapple with several inherent properties of the domain. First and most importantly, building data is *heterogeneous*. Buildings are characterized by one-off, ad-hoc conglomerations of different technologies from different vendors, assembled over time. This means that the specific data available about a building will be unique to that building and makes it difficult to generalize any one management solution across many buildings in a portfolio. To this end, we review recent work on metadata models for buildings which address these organizational challenges.

Secondly, buildings are *complex* systems, but not all the complexity is required for all uses of building data. The cyber-physical systems inside buildings enact a variety of different processes whose implementations are specific to that system and building. It is important to determine the proper level of detail for modelling a building so that important details are preserved, and non-essential information can be ignored.

Lastly, buildings experience constant *churn*. Buildings are not static entities; they are changed over time through retrofits, repairs and other means. If the data and metadata for a building are not kept abreast of this evolution, then data-driven use cases will operate on incomplete or incorrect information.

To this end, we review state-of-the-art data integration techniques which facilitate the creation and maintenance of data and metadata in buildings.

3.0 Data and Metadata Models

A **model** is a digital representation of a building that adopts a particular organization and structure to support certain modes of use. No model of data or metadata will be appropriate for all potential uses; rather, one must take into account the family of data-driven use cases when selecting or designing a data model. Some kinds of questions are easier or more efficient to answer with some models over others. A building will have many digital representations over its lifetime which are produced and maintained for different purposes (Fierro et al., 2020). Building information models such as gbXL and IFC make it possible to exchange geometric information about the building during design and construction. Modelica and the Control Description Language are representations which express simulations of the building and generic control sequences governing the building’s operation and thus facilitate the commissioning of a building. Each of these models falls in the category of *open standards* and thus are permissively licensed, freely available, and supported by ecosystems of commercial and open-source software solutions.

However, these models are rarely used during the operational phase of a building; instead, building management systems (BMS), building automation systems (BAS) and other operating systems for buildings leverage proprietary internal models which are rarely documented, lack consistent structure, and impede the extraction and use of the data they contain.

This is a challenge for data-driven smart buildings because the BMS/BAS is often the primary location of critical building telemetry (Bhattacharya et al. 2015). For this reason, we will focus on data and metadata management for the operational phase of a building.

In this section, we briefly outline the landscape of data and metadata models for smart buildings identify the mature and emerging approaches in the space along with commercial and open-source implementations. Finally, we identify the challenges in adopting state-of-the-art data and metadata models and what future opportunities are.

3.1.1. Role of Data and Metadata in Data-Driven Smart Buildings

We begin with a high-level picture of how data and metadata “move" through a representative data-driven building (Figure 3-1).

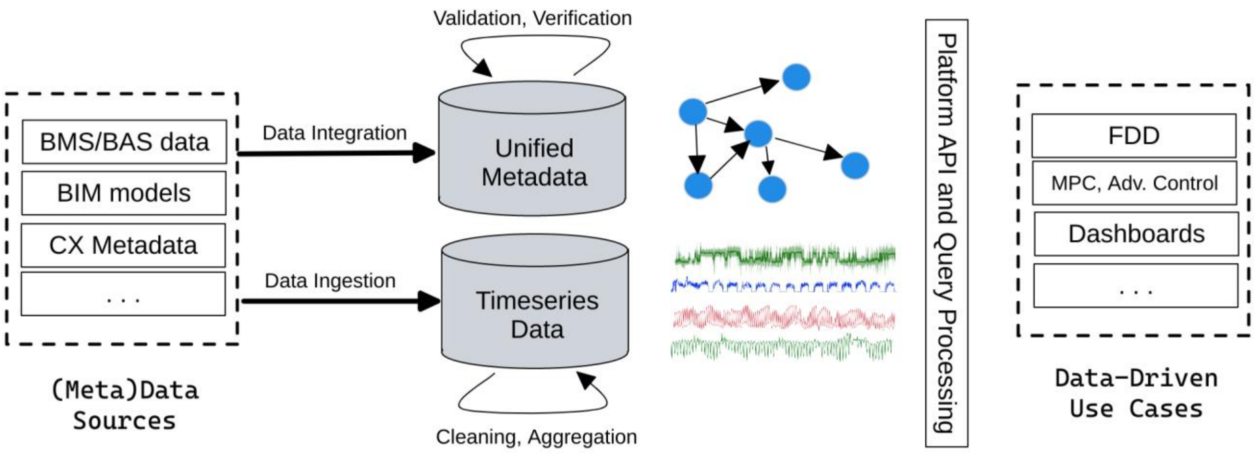

Figure 3-1. Metadata lifecycle.

Operational telemetry (i.e., *data*) represents the live status of the building and primarily comes from BMS and BAS deployments and is communicated over protocols like BACnet and OPC-UA. Telemetry is the time series data produced by sensors, actuators, alarms and other I/O points that is used in machine learning models, intelligent controls, fault detection and diagnosis processes, dashboards and other data-oriented processes. This data is typically stored in a *time series database*. Time series databases are software systems optimized for the storage and retrieval of continuously-growing sequences of timestamped measurements, statuses and observations. This data typically needs to be cleaned (to remove noisy or erroneous values) and aggregated so it can be consumed by downstream data processes. Time series databases also decouple consumers of data from the producers of data (e.g., sensors in a BMS), thus allowing software to remain agnostic to the particular protocols and formats used by a given building.

Metadata is information that describes useful properties of data sources. This includes immediate properties such as engineering units and sample rate but also broader *contextual* information such as how data is produced (e.g., what kind of sensor is it?), where the data is produced (e.g., where is the data source located?), and how the data relates to other parts of the building (e.g., how is this data used by the building?).

A metadata model defines a structure for this information; however, designing an effective metadata model is difficult. The only truly representative model of a building is one that is 1-1 with every physical aspect of the building and its environment, which is intractable. A common adage is “all models are wrong, but some are useful"; this suggests that a metadata model must choose how it wants to *abstract*, or simplify, the building.

Effective data and metadata models are crucial for enabling data-driven smart buildings. Data must be organized so it can be accessed efficiently by a wide array of use cases whose implementations can remain agnostic of the actual data source. Metadata allows the software to reason dynamically about which data sources in a building are relevant for an application. Without metadata, data-driven use cases must be *hard-coded* to the particular data sources available for each building, and a human operator must manually configure the use case logic to the idiosyncrasies of each deployment site. This impedes the large-scale development and deployment of data-driven use cases (Fierro, 2021; Bergmann et al., 2020).

3.1.2. Commercial and Open-Source Landscape

The bulk of recent innovations in data-management for buildings have focused on the *metadata models* for data-driven use cases. Most digital control systems for buildings --- including building management systems (BMS), building automation systems (BAS), and energy management systems (EMS) --- use flat, alphanumeric strings to describe data sources (Bhattacharya et al., 2015). Figure 3-2 depicts one way of organizing these metadata models according to what aspects of the building they model and what kind of inquiries they support on behalf of downstream applications.

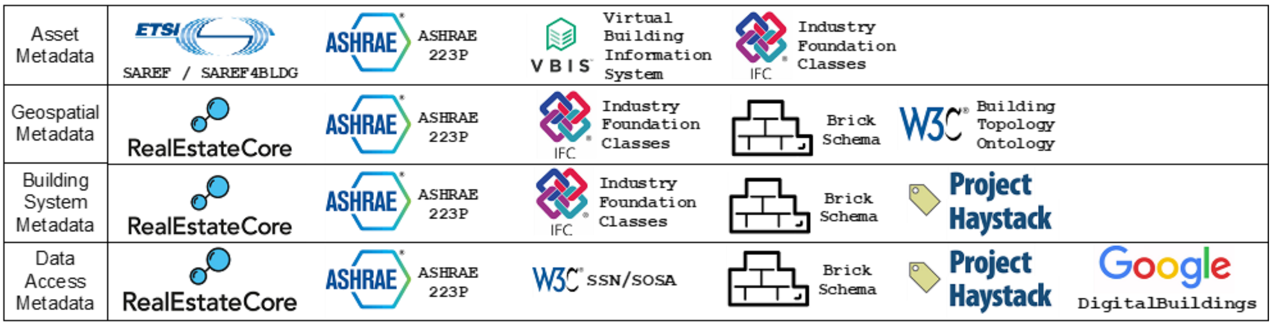

Figure 3-2. An overview of metadata representations and their respective features.

Project Haystack[1] is an open-source metadata effort to use a discrete dictionary of *tags* to annotate these data streams with consistent terminology. SkyFoundry[2] contributes to the development of Project Haystack and offers a complete data platform providing ingestion, tagging and analysis of building data. Other companies[3], including Siemens and J2 Innovations, participate in the development of Project Haystack and have incorporated elements of it into their own products.

Brick[4] is an open-source metadata effort that uses existing *semantic web* technology to implement a consistent and verifiable representation of a building as a graph. Five companies, including Johnson Controls and Schneider Electric, have joined the open industrial consortium formed around Brick[5]. Brick has also been incorporated into large-scale data-sharing platforms like CSIRO's Smart Building Data Clearing House[6] and Mortar (Fierro et al., 2019).

[1] https://project-haystack.org/
[2] https://skyfoundry.com/
[3] https://project-haystack.org/about
[4] https://brickschema.org
[5] https://brickschema.org/consortium/.
[6] https://www.ihub.org.au/ihub-initiatives/smart-building-data-clearing-house

RealEstateCore[7] is an open-source metadata effort also based on semantic web technology that focuses on asset and property management. Several companies and organizations have signed onto the RealEstateCore Consortium, including Idun Real Estate Solutions, RISE and Willow Incorporated. The most notable adoption of RealEstateCore is by Microsoft, which uses the ontology as part of their Azure Digital Twin system, also available through Willow Incorporated.

Google Digital Buildings[8] is another entry in the metadata space that focuses on structured representations of the data needed to support applications. It is being used internally at Google to support their building portfolio. Google Digital Buildings can be exported to a form compatible with the semantic Web, but relies on custom formats and tooling for most of its features.

ASHRAE is developing a metadata standard entitled “Semantic Data Model for Analytics and Automation Applications in Buildings", also referred to by its identifier **223P**, which represents detailed, low-level information about the composition and topology of buildings and their subsystems.

A variety of other metadata ontologies related to buildings are available today which are open-source, freely available and permissively licensed; **BOT** (Rasmussen et al., 2017), **SAREF** (Poveda-Villalón and García-Castro 2018), **SSN/SOSA** (Haller et al. 2019) are the most prominent of these.

Other information management technologies have been developed for other stages of a building's lifecycle and other aspects of building operations and management. **VBIS**[9], Omniclass, Uniclass, COBie all deal with asset management and provide means of classifying and organizing equipment.

Most of the above metadata solutions deal in some way with the building telemetry that fuels intelligent, data-driven use cases. A few of the solutions are co-designed with specific platform offerings that manage this data --- Project Haystack and the Azure Digital Twins offering of RealEstateCore --- but others (such as Brick) are designed to work flexibly with many different data management platforms.

There are numerous data management solutions available in the open-source and commercial landscape that are sufficient for this task. These include timeseries databases such as **InfluxDB**[10], **TimescaleDB**[11], and **OpenTSDB**[12]. Direct integration between metadata ontologies and these platforms are largely works-in-progress or non-existent; however, such efforts are largely in reach of development teams.

3.1.3. Barriers to Adoption and Challenges

There are several interrelated factors which pose barriers to the adoption of data and metadata models that enable data-driven smart buildings.

The first barrier is that data and metadata models designed for data-driven smart buildings are relatively nascent technologies. At this time, many digital control systems for buildings do not incorporate sophisticated metadata models for buildings due to limitations of the underlying communication protocol or an established focus on “expert systems” rather than data-driven processes (such as those described in Chapter 4). This situation is changing: modern software platforms for buildings (3.1.2) are beginning to incorporate modern data and metadata models into their solutions.

[7] https://www.realestatecore.io/
[8] https://github.com/google/digitalbuildings
[9] https://vbis.com.au/
[10] https://www.influxdata.com/
[11] https://www.timescale.com/
[12] http://opentsdb.net/

Another barrier to adoption is the wide choice of data and metadata models available today. There is no metadata model that is appropriate for all possible data-driven use cases, and many of the existing models exhibit trade-offs which are not always obvious. As a result, it is difficult for non-experts to enumerate, select and evaluate these models against each other. Potential adopters of standard data and metadata models may hesitate out of an understandable desire to avoid a poor investment.

The third barrier is a lack of turnkey solutions for working with metadata. Data integration systems are required to create, curate and maintain the data and metadata models. Data is comparatively “easy” to manage: there is a relatively high degree of consensus in the industry around a set of communication protocols for communicating with the digital components in a building, so there is little need to innovate on or develop in-house solutions to deal with data. These protocols include BACnet, OPC-UA and Modbus. Metadata models are more difficult to create, mostly due to the fact that they represent information that is not explicitly or consistently captured by existing building systems. We will explore the difficulties of metadata integration below.

3.2. Data Integration

A crucial component to leveraging data and metadata for enabling data-driven smart buildings is how the data and metadata are “brought in” to a software platform that makes them available to developers, users and other stakeholder data consumers. The heterogeneity of buildings is the biggest challenge here — the sheer diversity of buildings means it is difficult to create a “one size fits all” solution — but it is also the greatest opportunity.

Data integration is the process by which the jumble of heterogeneous information for a building is lifted into a clean and standard form that is easily accessible by software. The process of data integration incorporates the cleaning of data and the extraction of structured information into a metadata representation such as the ontologies above. These metadata representations can then be accessed by applications in order to realize data-driven smart buildings.

3.2.1. Current Challenges

There is a broad array of data integration techniques available. Due to the heterogeneity of buildings, specifically the diversity of their *existing* digital representations, there is no "silver bullet" technique that will work in all scenarios, nor is there a single turnkey solution or platform that will serve all buildings equally well. Familiarity with the strengths and weaknesses of these techniques is required to adapt these techniques to the particular idiosyncrasies of each deployment site.

First, we present a high-level classification of existing digital representations of buildings. *Building Information Models* (BIM) are representations of buildings broadly designed to exchange information during the architecture, design and construction phases of a building. These models — informed by standards such as Green Building XML and Industry Foundation Classes or proprietary technologies such as Autodesk's Revit — capture the geometry of building components and the topology of internal systems such as HVAC, plumbing and electrical. The existence and quality of these models vary wildly as they are informed by regional practices and regulations as well as the expertise of the modelers. These models may also be out of date or hard to find; in some countries, it is rare for the BIM to be “handed off” to the owners or managers of the building after completion. Nonetheless, when available, BIMs are the most complete and *structured* representation of buildings.

Operational systems such as building automation systems (BAS), building management systems (BMS), energy management systems (EMS) and other networked building operating systems are another source of metadata. These systems operate by reading from and writing to hundreds or thousands of input/output "points" — including sensors, setpoints, alarms and direct commands — which serve as the cyber-physical interface between software and the equipment in the building. These points are usually labelled by the engineers who configure the operational system to describe the point to the eventual users of the system. However, due to historical constraints on the capabilities of digital device controllers and incumbent network protocols, these labels are usually short, alphanumeric strings that contain limited information. Furthermore, there are no standards for the format of these labels or the abbreviations used within. This presents challenges for the extraction of useful metadata.

3.2.2. State of the Art Techniques and Solutions

There is a rich history of academic and commercial solutions to the data integration problem. For brevity, we focus on the techniques that have been developed specifically for integration of metadata in buildings. Many of these techniques borrow from or improve upon more general existing solutions.

Direct translation and ETL (extract-transform-load) techniques operate by ingesting well-defined, machine-readable information, extracting necessary details and relationships, and outputting metadata in the desired format. As explored in Lange et al. (2018), Fierro et al. (2020), Pauwels and Terkaj (2016), this works best when BIMs or asset management data is available. There is active work on producing translations between several of the ontology-based metadata representations explored above. Such translations are characterized by being highly automated and delivering reliable, unambiguous results.

Inference-based techniques are more commonly used when the available digital metadata is messy or unstructured, as typified by point labels. Academic work Bhattacharya et al. (2015), Koh et al. (2018) leverage human-in-the-loop techniques, which learn the topology and composition of building subsystems by asking human experts what information can be extracted from representative point labels and then generalizing that feedback to the rest of the building. Additionally, Waterworth et al. (2021) have explored using sophisticated language models to replace some of the required input from a human expert. These efforts are more effective the more information is contained within building point labels, which is a site-specific characteristic. Sometimes the relationships between equipment in a building can be uncovered by perturbing the building with unusual control inputs, as explored in Pritoni et al. (2015). Work has also explored inferring the presence of and relationships between equipment using historical telemetry Lin et al. (2019), and other research (Shi et al., 2019) shows how such data-driven techniques can complement those that work with point labels.

Wrapper-Mediator is a third approach to data integration that focuses on accessing metadata contained in external representations without having to translate that metadata to the target schema. Instead, a "wrapper" process provides access to some external metadata source; the wrapper performs on-demand translation of the metadata in that source to a destination schema specified by the user of the service. This is a promising design for two reasons. First, not all metadata representations are appropriate for all kinds of metadata. For example, BIMs have more natural expressions of geometry and spatial relationships than graph-based metadata representations; it is more natural for a wrapper process to rephrase incoming semantic queries ("which room is next to room 410") in terms of underlying BIM geometries, rather than exhaustively mining every possible geometric relationship from the BIM and replicating that in a graph representation. Second, wrapper-mediator solutions present a way for existing metadata representations to be made *interoperable* without having to rigorously maintain a translation document or process that captures all possible equivalencies between two given representations.

3.3 Conclusion

Proper management of data and metadata is critical to realizing data-driven smart buildings at scale. The solutions that dominate the existing building stock are ad-hoc and non-standard and thus require costly integration to extract value. This section has outlined open-source and commercial efforts which can provide access to the growing volume of data produced by buildings, store it efficiently for later analysis, and annotate it with descriptive semantic metadata. Semantic metadata captures the context of the telemetry used for data-driven use cases. Semantic metadata standards give structure to this information by providing standard concept definitions, validation rules, and families of rich relationships necessary for describing data in a consistent and interpretable way.

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4. Data-Driven Control Strategies

- How can “big data” help in improving building operation
- Data-driven modelling techniques for MPC
- Challenges: data requirements for control applications
- Model-free approaches
- Future opportunities

4.0 Why Data-Driven Control Strategies

The ever-increasing availability of data from building automation systems and other sources, along with the computational power that enables storing and analysing this data, have opened numerous opportunities to enhance the operation of HVAC and other systems both inside and outside buildings. At a dizzying speed, new possibilities emerge to collect data that may be useful, from the interaction of occupants with lighting systems to the use of additional instrumentation in heating and cooling equipment. Information from hundreds or thousands of variables collected from diverse locations throughout the building make it possible to correct, learn and thus fine-tune the operation of buildings at many different levels and for many diverse applications. The adage of “you cannot manage what you cannot measure” remains true. Thankfully, the number of things that are measured in a building keeps increasing, and the potential to improve building operation is virtually limitless.

For example, at the supervisory control level, data can be used to better understand how to adjust temperature setpoint profiles with the objective of reducing electric peak loads and reducing GHG emissions. At the local control level (within an office or a room) data collected from temperature sensors, occupancy sensors, supply air temperatures, etc. can help in selecting optimal values for the operation of air-handling units, radiators, baseboard heaters and radiant floors.

A key element in the usefulness of data for control applications is the fact that it opens the door to the creation of a reliable building model or “digital twin”. A building model allows testing “what if" scenarios under different weather patterns, occupancy profiles and unexpected events. While it is possible to generate a model based on basic assumptions, a model resting on the solid foundation of measured data can provide building operators and managers with a priceless tool assisting in decision-making.

This abundance of data remains largely unexploited in building controls. While in other domains of human activity, the value of data is clear, building engineering has been comparably slower to adopt data as a cornerstone of new developments.

4.1 Model-Based Predictive Control

Model-based controls, and more specifically model-based *predictive* controls (MPC) are at the core of the idea of leveraging data for improving models. MPC is a control methodology whereby a *model* of a system (in this case, a building or its mechanical plant) is used along with weather and occupancy forecasts to optimize the control actions with regards to an objective function (cost, GHG emissions, energy use, etc.) (Figure 4-1). The “control-oriented model” (the one used in optimization routines) of the system is created by data from the building automation system, historical weather and sometimes from detailed building simulation tools. For a detailed overview of MPC in buildings, the reader is referred to the excellent review paper by Drgona et al. (2020).

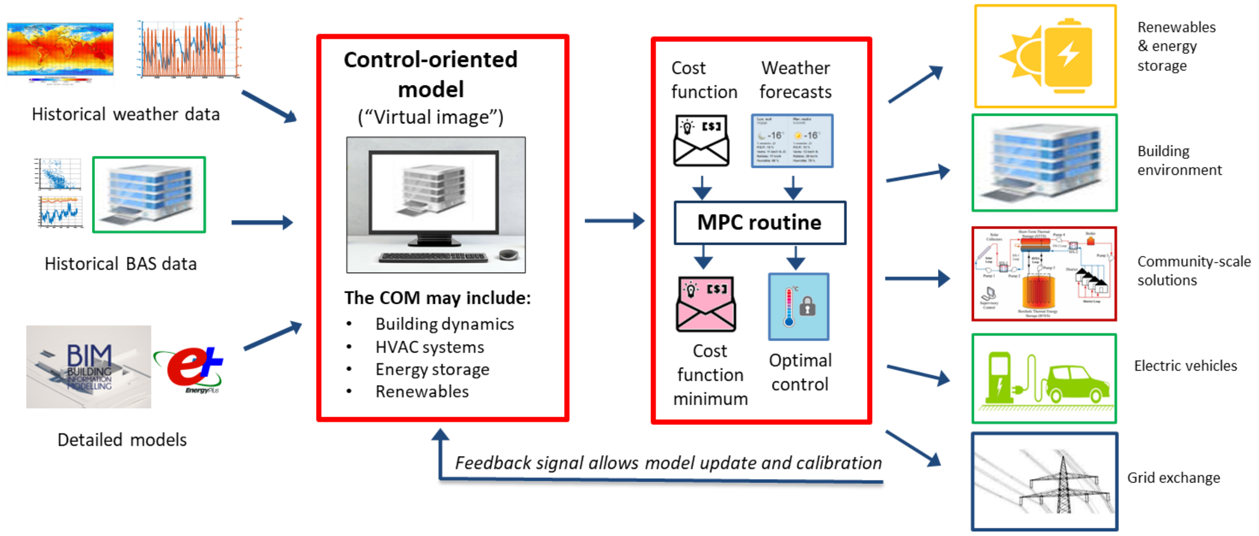

Figure 4-1. Concept of Model-Based Predictive Control.

The most difficult step is the creation of the control-oriented model. Developing the building energy models has been called the "bottleneck of the whole procedure" of MPC by Prívara et al. (2012). During a preliminary survey carried out in the context of Annex 81, the development of the model was mentioned as the main obstacle in the creation of an MPC strategy, often taking over 50% of the time required in the development of the project (Figure 4-2). In the end, the effectiveness of MPC reflects the accuracy of the predictions of the model employed.

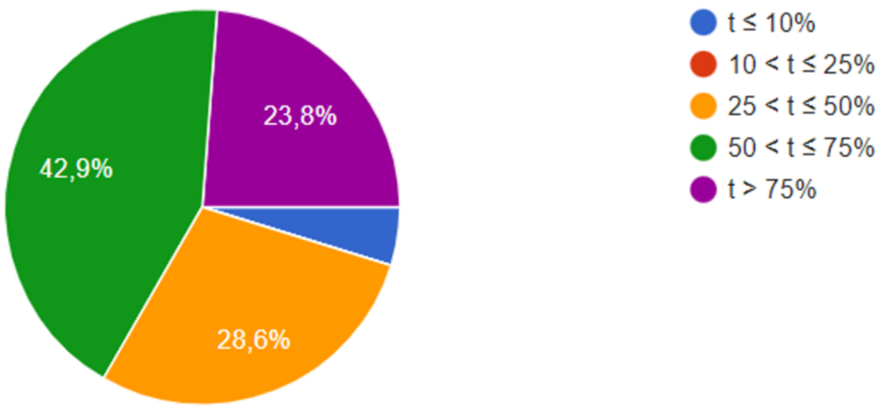

Figure 4-2. Percentage of time of a model-based predictive control project spent in model development.

The following pages discussed some modelling approaches used in MPC for buildings.

4.2 Models for Controls

4.3.1 Grey-Box Approaches

Grey-box modelling is very popular for MPC and control-oriented modelling in general. Today, grey-box models are also called data-driven digital twins. The grey-box framework bridges the gap between models based on first principles (*white-box* models) and models based on solely on data (*black-box* models) as indicated in Figure 4-3.

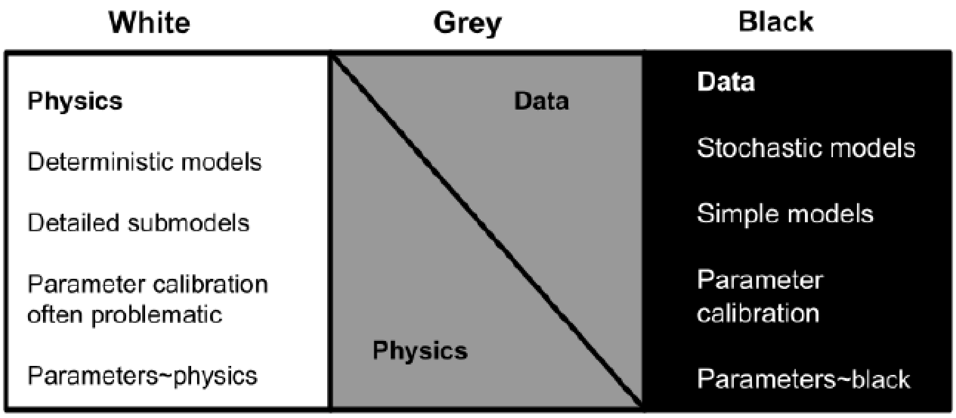

Figure 4-3. Grey-box modelling bridges the gap between white and black-box modelling.

For the typical applications related to control-oriented modelling for buildings the grey-box model is formulated as a lumped-parameter model, and in the linear case this model is often described using RC networks. See for instance Bacher and Madsen (2011) on a methodology for the identification of RC network-formulated grey-box models for buildings.

Grey-box models are typically formulated as a state space model where the dynamics of the states is described in continuous time by a set of stochastic differential equations (SDEs, *system equations*).

The discrete-time observations are related to the states by a set of static equations (observation equations). Hence, a grey-box is formulated as continuous-discrete time stochastic state-space model in the form:

$$\mathrm{d}x(t) = \underbrace{f(x(t), u(t), d(t), t)\mathrm{d}t}_{\text{Drift}} + \underbrace{g(x(t), u(t), d(t), t)\mathrm{d}\omega(t)}_{\text{Diffusion}} \tag{4.1}$$

$$y_k = h\big(x(t_k)\big) + v_k\,, \qquad v_k \sim N(0, R_v) \tag{4.2}$$

Where x is the system vector, ω is a standard Wiener process (also often called a Brownian motion), and f and g are the drift and diffusion function, respectively, h is the observation function and v_k is the observation noise. The *drift function* is the deterministic part of the SDE, whereas the *diffusion function* describes all the uncertainties not properly described in the drift.

If the system in (4.1)-(4.2) is linear, the model is written:

$$\mathrm{d}x(t) = \big(Ax(t) + Bu(t) + Ed(t)\big)\mathrm{d}t + \Sigma \mathrm{d}\omega(t) \tag{4.3}$$

$$y_k = Cx(t_k) + v_k\,, \qquad v_k \sim N(0, R_v) \tag{4.4}$$

where A, B, E, C and Σ are matrices governing the state evolution, input, disturbance, observation and noise, respectively.

Modelling physical systems using SDEs provides a natural method to represent the phenomenon as it evolves in continuous time. In contrast to discrete-time models, prior physical knowledge about the system can rather easily be included, and the estimated parameters do not depend on the sampling time.

There are many reasons for introducing the system noise (the diffusion term):

- *Modelling approximations*. For example, the dynamics, as described by the drift term, might approximate the true system.
- *Unrecognised and unmodeled inputs*. Some variables which are not considered, such as wind speed, may affect the system.
- *Noise in measurements of input variables*. In such cases, the measured input signals are regarded as the actual input to the system, and the deviation from the true input is described by the noise term.

In the observation equation, a noise term is also introduced. The reason for this noise term is:

- *Noise in measurement of output variables*. The sensors that measure the output signals are affected by noise and drift.

It seems reasonable to assume that the system noise and the measurement noise are independent.

A popular software package used for grey-box modelling is CTSM-R (Juhl et al., 2016a, Juhl et al., 2016). The mathematical and statistical methods used are described in Kristensen et al. (2004).

The performance of certainty-equivalent controllers such as conventional MPC for smart energy systems depends critically on accurate disturbance forecasts. The use of grey-box modelling also offers methods for embedding advanced weather disturbance models in model predictive control (MPC) of energy consumption and climate management in buildings as described in Thilker et al. (2021).

4.2.2 Linear Time Series Models

In this section we will introduce the most frequently used linear time series models. We will describe how they can be obtained as simplifications of the linear and time-invariant grey-box model introduced in the previous section.

We shall first introduce the state space model, and then illustrate how the Box-Jenkins transfer function model as well as the ARMAX model is obtained by eliminating the state vector. Finally, the impulse response and frequency response functions for linear time series will be introduced.

For more information on model identification, model evaluation as well as methods for parameter estimation we refer to (Madsen, 2007).

4.2.2.1 State-Space Models

From the abovementioned continuous-discrete time linear and time-invariant state-space model the discrete time linear state space model is obtained

$$x_{k+1} = \Phi x_k + \Gamma u_k + v_k \tag{4.5}$$

$$y_k = Cx_k + Du_k + e_k \tag{4.6}$$

With $\Phi = \exp(A\tau)$, $\Gamma = \int_0^\tau exp(As)\, B\, ds$, $v_k = \int_k^{k+\tau} \exp(A(k+\tau-s)\sigma)\, d\omega_s$, where τ is the sampling time.

Let us now briefly compare the model with the previously considered continuous time linear state space model. It can be noticed that due to the discrete time formulation of the dynamics we have:

- Assumed equidistant data, and the possibility of using irregular sampling is lost.
- The direct physical interpretation of the parameters is lost.
- A much higher number of parameters may typically be needed, which implies lower efficiency and lower robustness.

The discrete time linear stochastic state-space model is often used for control purposes.

4.2.2.2 Transfer function models

The equivalent transfer function model is readily obtained by eliminating the state vector, i.e. we obtain the **Box-Jenkins transfer function model**:

$$y(z) = (C(zI - \Phi)^{-1}\Gamma + D)u(z) \tag{4.7}$$

$$+\big(C(zI - \Phi)^{-1}v(z) + e(z)\big) \tag{4.8}$$

$$= \frac{\omega(z^{-1})}{\rho(z^{-1})}u(z) + \frac{\theta(z^{-1})}{\phi(z^{-1})}\epsilon(z) \tag{4.9}$$

For $\rho(z^{-1}) = \phi(z^{-1})$ we obtain the well-known **ARMAX model:**

$$\phi(z^{-1})y_k = \omega(z^{-1})u_k + \theta(z^{-1})\epsilon_k \tag{4.10}$$

where z is the z-transform variable.

Notice that compared to the discrete-time state-space model we must conclude that:

- The decomposition of the error into process error and measurement error is lost.
- The state variable has disappeared.

The ARMAX model is frequently used for control purposes, and for instance the Minimum-Variance Controller is easily derived from ARMAX models; see e.g., (Madsen, 2007).

4.2.2.3 Impulse and Frequency Response Models

Let us now introduce the non-parametric descriptions of linear time series relations in both time- and frequency domain. A non-parametric time-domain linear model description is obtained by polynomial division, i.e.

$$y_k = \sum_{i=0}^{\infty} h_i u_{k-i} + N_k \tag{4.11}$$

where $\mathrm{N_k}$ is a correlated error sequence. The sequence $\mathrm{N_k}$ is the **impulse response (matrix) function**.

The frequency (or z) domain counterpart is:

$$y(z) = H(z)u(z) + N(z) \tag{4.12}$$

where $\mathrm{H(z)}$ is the transfer function, and for $z = e^{i\omega}$ we obtain **the frequency response function (gain and phase)**.

Compared to the previously considered transfer function model we must now conclude that:

- The parametric description of the error is lost.
- The non-parametric model hides the number of time constants (model order), etc.

Impulse and frequency response functions are often used in analysing the properties of controllers.

4.2.3 Black-box Approaches

In recent years, black-box models based on machine learning methods have been employed to rapidly obtain a model for a particular building. This method offers accurate results provided that the measured data is sufficiently accurate. Some reviews in the topic of *machine learning* related to building energy modelling include the ones by (Afram et al., 2017) and Maddalena et al. (2020). Artificial intelligence black-box models have become a popular pathway among field practitioners.

Black-box models represent a "mapping" of sorts between inputs and outputs established with a training dataset. Relying solely on the dataset to train a black-box model implies a potential challenge: the model accurately predicts the data it has already "seen" but lacks extrapolation ability. Black-box models can achieve a great deal of accuracy, even with non-linear phenomena. Although they may be obtained systematically, they cannot be easily exported directly from one building to another. Furthermore, black-box models are not ideal candidates to optimize the operation of buildings because they are usually trained on data from conventional, "business as usual" control strategies (Afram and Janabi-Sharifi, 2014).

4.3 Challenges for MPC

4.3.1 System identification of Appropriate Models

System identification refers to the process of identifying the values of the parameters in a model based on the available data. Successful system identification using measured data encompasses the concepts of structural and data-dependent identifiability (a measure of the possibility of obtaining an accurate model from the available data).

- *Structural identifiability* relates the identifiability of a model to its structure, and it depends only on the model order and the parameter set (Agbi et al., 2012). A model with very few parameters and low order may lack the ability to accurately describe the physical phenomena that define the system. On the other hand, a model with too many parameters — or equivalently of too high an order — is an over-parameterized model. This parameter redundancy makes multiple combinations of parameter values to correspond to the same model output, therefore having multiple ”optimal” solutions of parameter sets. In building modelling, choosing the order and the structure of the model is not a straightforward task. More often than not, it requires professional experience and expertise and there is no solid proof that the resulting model is the best model possible for the system at hand with the available data (Li et al., 2021). The most common reason for identifiability problems is an over-parameterized model (Brastein et al. [2018], Li et al. [2021], Yi and Park [2021]).

- *Data-dependent identifiability* relates the identifiability of a model to the data it is calibrated with and it only depends on the initial state of the system and its inputs (Agbi et al, 2012). It expresses that even if a model is structurally identifiable, the dataset used may be of poor quality and not contain enough thermal dynamics information for the model calibration. Ljung (1999) proposes to excite the system with a variety of inputs in an open-loop fashion in order to ensure that the dataset will contain enough information for the system identification.

In practice, both the structural and data-dependent identifiability of a model are not a binary state, i.e., they extend over the whole range from identifiable to non-identifiable.

A pressing need in the world of data-driven MPC in buildings is how to accelerate the uptake of this technology. In other words: how to increase its scalability. As mentioned above, model creation is the main bottleneck of this technology. A concept that has been put forth is the idea of using *control-oriented archetypes* to accelerate the deployment of MPC (Candanedo et al., 2022). Control-oriented archetypes are simplified representative models that contain features of a generic building type. While not identical to a building in particular, archetype models can be used in the development of policies with a general applicability.

4.4 BOPTEST

Needs for advanced and improved control strategies in building and district energy systems are growing due to requirements for reducing energy use, greenhouse gas emissions, and operating costs, providing flexibility to the electrical grid, as well as ensuring performance of novel hybrid and collective system architectures. Examples of such control strategies are advanced rule-based control, and the abovementioned Model Predictive Control (MPC) (Drgona et al., 2020), and Reinforcement Learning (Wang and Hong, 2020). However, while these and other control strategies show promise, two challenges slow their widespread adoption:

- The performance of each control strategy is typically demonstrated on individualized case studies and quantified using different performance indicators, making it difficult to properly benchmark and compare their performance, identify the most promising approaches, and identify needed further development.
- Demonstrations in real buildings and district energy systems pose large operational risks and difficult environments for controlled experiments.

The building simulation community can address these challenges by providing suites of publicly available, high-fidelity simulation models, called emulators, to be used for benchmarking control strategies. Furthermore, providing a comprehensive framework to deploy, interact with, and generate key performance indicators (KPI) from these emulators would ensure their benchmarking capability and make them readily available to related control and data science fields outside of the BPS community. There exists precedent for such an approach within the building simulation field with the development of the BESTEST (Judkoff and Neymark, 1995) and subsequent ASHRAE Standard 140 (ASHRAE 2011) as well as the optimization fields (e.g. Decision Tree for Optimization Software (Mittelman 2022) and data science (e.g. OpenAI Gym, 2022).

Work is underway on the envisioned framework and emulators, called the Building Optimization Testing Framework (BOPTEST), which is developed and available open-source at https://github.com/ibpsa/project1-boptest. The framework is described in detail in (Blum et al., 2021) and has been used in (Arroyo et al., 2020, Arroyo et al., 2022, Bünning et al., 2021, Huang et al., 2018, Walnum et al., 2020, Yang et al., 2020, Zanetti et al., 2022).

BOPTEST (Figure 4-4) consists of a run-time environment (RTE) deployed using *Docker* (Docker, 2023) that provides a rapidly accessible and repeatable environment to deploy building emulators, select test scenarios, manage control signals and measurement outputs, simulate the responses of the emulators to external control signals, receive boundary condition forecasts for predictive controllers, and calculate KPIs, all through a generally accessible RESTful HTTP API.

High-fidelity, well-documented, building emulators, so called “test cases”, are implemented using *Modelica* (Mattson and Elmquist, 1997), especially using the Modelica Buildings (Wetter et al., 2014) and IDEAS (Jorissen et al., 2018) libraries, and compiled into Functional Mockup Units (FMU) (Blochwitz et al., 2011) for simulation within the RTE using the Pyfmi Python package (Andersson et al., 2016). The use of Modelica allows for modeling fluid pressure-flow networks and control logic explicitly, as well as the use of variable time-step solvers, which are critical for capturing dynamic system response to control signals in realistic ways.

Test case models also contain embedded control such that test controllers can choose set points and actuator signals to overwrite at the supervisory or local loop levels. In addition to the dynamic model, test case FMUs also contain all necessary boundary conditions to simulate the model (such as weather and internal load schedules) as well as calculate relevant KPIs (such as electricity prices and carbon emission factors). Finally, the RTE calculates and reports a standard set of KPIs including energy use, energy cost, peak demand, and thermal and air quality discomfort. In addition to core framework and emulator development, additional development is making BOPTEST available as a web-service (https://github.com/NREL/boptest-service), providing an OpenAI Gym interface (Arroyo et al., 2021), providing a BACnet interface and integrating semantic modeling (Fierro, 2022), and providing an online dashboard to share and sort results.

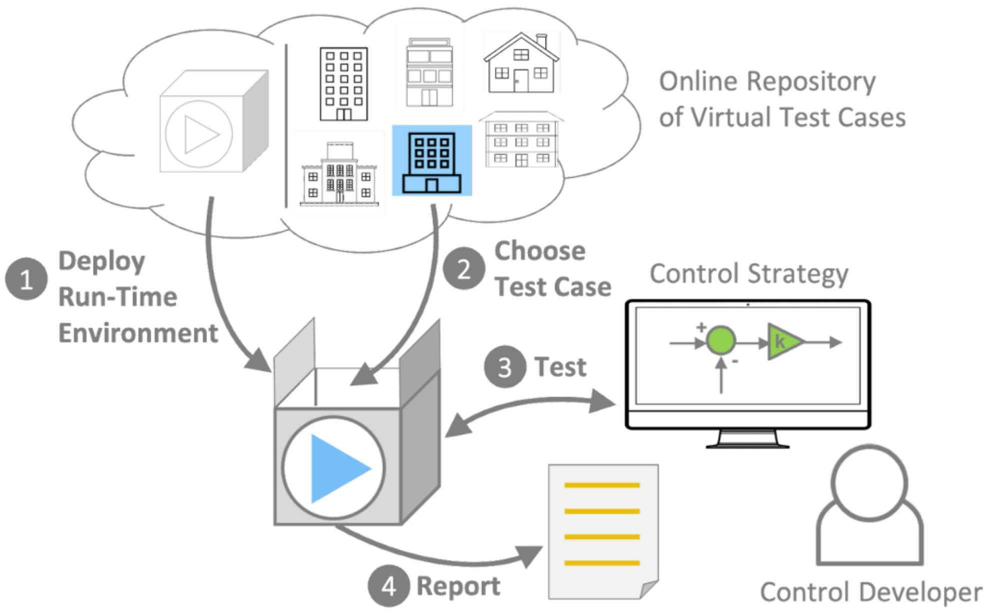

Figure 4-4. BOPTEST Concept.

4.5 Reinforcement Learning

Reinforcement learning is a machine learning concept whereby data from numerous scenarios can used to train a controller to select control actions that maximize a “reward” or apply a “punishment” under a given set of conditions. Reinforcement learning is quite effective as a means to select the best possible control actions. If sufficient data including a vast universe of diverse conditions are available, then the RL algorithm can be trained without a model. In this sense, RL is sometimes referred to as a “model-free" method. If not enough data are available to train the RL algorithm, a simulation tool often called “AI gym”, intended to generate synthetic data under different a vast range of conditions, can be used.

Vásquez-Canteli and Nagy (2019) reviewed studies using Reinforcement Learning for Demand Response until the year 2018 and found that most of them focus on single-agent systems and stationary environments. They emphasize the importance of non-stationary environments because of the presence of multiple consumer agents (i.e., buildings) affecting the energy consumption of a grid during the peak hours. They identified testing in real systems (and not simulations) as one of the potential paths for future research, and specifically analyzing reliability, adaptability, scalability and learning speed.

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5. Real-Time Implementation of Control and Forecasting

- How are forecasting and control related?
- Disturbance forecasting for building thermal control
- Economic MPC versus linear quadratic MPC
- Real life example: MPC of thermal conditions of a school building

5.0 Relationship between Forecasting and Control

For predictive control, it is central to have available forecasts of so-called *disturbances* that appear in the system. A disturbance is a non-stochastic, dynamical system input which is not controllable. The process generating the disturbances might be (and usually is) stochastic, but such errors are often disregarded or described by a white-noise process. A disturbance is thus a significant *predictive* input to the system that *disturbs* the dynamics. If such disturbances are disregarded in a predictive control setup, the control performance is doomed to be sub-optimal (or even worse than status quo) since many underlying assumptions in the control and modelling framework becomes terribly wrong.

Reference tracking is a common task in control applications (Bagterp Jørgensen et al. 2012) and is used in many layers of the energy grids to balance electricity loads, avoid voltage overload and congestion etc (Xie et al., 2020). It is thus a diverse and well-studied controller for many applications. In certain settings, it has attractive properties that ensure fast and robust optimisation performance, which is extremely important in real-time implementations.

In the following, we explain/illustrate why forecasts in a certain form is key to obtain optimal performance. For a reference-tracking predictive controller, a popular objective is the following quadratic function:

$$\min_{\boldsymbol{u}_t} \quad \phi = \int_0^T \mathbb{E}[\|\boldsymbol{z}_t(\boldsymbol{u}_t) - \boldsymbol{r}_t\|_2^2 | \mathcal{Y}] \, \mathrm{d}t \tag{5.1}$$

In the above:

- $z_t(u_t)$ is the system we wish to control with an input $u(t)$
- r_t is the reference point at which we wish to stabilise the system.
- ϕ is the objective function, which has the purpose of making control solutions comparable.
- $\|z_t(u_t) - r_t\|_2^2$ is the quadratic distance between z_t and r_t
- T is the prediction horizon, that is how far into the future the controller considers. Ψ is all the past history of the system, input, and disturbances. Therefore, in the above optimal control problem, it is assumed that all history till the current time instance is known --- which is usually a fair assumption. Writing out the objective function, the properties of the objective function appears:

$$\mathbb{E}\left[\|\boldsymbol{z}_t(\boldsymbol{u}_t) - \boldsymbol{r}_t\|_2^2 \,|\, \mathcal{Y}\right] = \mathbb{V}\left[\boldsymbol{z}_t(\boldsymbol{u}_t)|\mathcal{Y}\right] + \|\mathbb{E}[\boldsymbol{z}_t(\boldsymbol{u}_t)|\mathcal{Y}] - \boldsymbol{r}_t\|_2^2 \tag{5.2}$$

The objective function appears as a weight between the variation of the system and the deviation from the reference point. The solution requires us to estimate the *conditional moments* of the system, $E[z_t(u_t)|\mathcal{Y}_{\mathscr{k}}]$ and $V[z_t(u_t)|\mathcal{Y}_{\mathscr{k}}]$. This implies that we need to forecast the *conditional expectations* of the disturbances of the system. This is a significant requirement and relates the solution to the optimal control problem to the forecasts that are needed to solve it.

In the following, we review the current standards for dealing with disturbances in control applications of smart buildings, which often is not predictive. We also review the suggestions and proposals regarding predictive forecasting in control applications in the literature.

5.1.1. Forecasting for Data-Driven Building Control

In predictive control of buildings---in order to account for the future conditions in the HVAC operations planning---it is necessary to *forecast* the future weather conditions (Thilker et al., 2021c). In particular, solar radiation and the outdoor air temperature are important elements to know beforehand. The coming sections cast light on the current standards for forecasting these.

5.1.2. Solar Radiation Forecasting

Solar radiation is by far the most important disturbance for short-term purposes due to the large amounts of power it delivers in short time (Madsen and Holst, 1995; Chen, 2011). Hence the importance of accurately forecasting the solar radiation on a short-term. But global solar radiation is not a standard parameter to deliver by meteorological institutes -- the literature thus proposes various methods to do this. Physically, the amount of radiation that hits Earth's surface is given by Lambert Beer's law (Paltridge and Platt, 1977).

$$I_G = I_0 \exp\left(\int_1 \mu(x) \mathrm{d}\, x\right) \tag{5.3}$$

where I_0 is the solar radiation emitted by the sun, μ is the attenuation of the rays, which is dependent on the atmospheric density. The latter, however, poses a difficulty since it is near impossible to estimate μ as a function of the atmospheric height. Instead, the term $\int_1 \mu(x) \mathrm{d}\, x$ is usually estimated based on the cloud cover (since it is the number one dependence). Models based on Eq. 5.3 exist in various forms due to its simplicity (Madsen, 1985, Dozier, 1980, Dai and Fang, 2014).

The literature proposes various grey-box related models as well. AR and ARX models are popular modelling schemes for solar radiation estimation (Amaro e Silva and C. Brito, 2018, Boland, 2015, Bacher et al., 2009). These are simple models where the estimated parameters are relatively easy to interpret compared to more advanced methods. Bacher et al. (2009) formulates auto-regressive (AR) and AR with exogenous inputs (ARX) models for predicting short-term solar radiation. They also investigate the importance of meteorological forecasts related to short-term forecasting. They find that the available solar observation is the most important input to the model compared to the meteorological forecasts. For long-term forecasting, however, meteorological forecasts become the most important input.

Models based on ANNs or random forests are also becoming increasingly popular for forecasting disturbances and modelling (Finck et al., 2019, Pang et al., 2020, Lago et al., 2018, Benali et al., 2019). A typical method is to use a feed-forward ANN using inputs such as the current time, cloud cover, and related climatic parameters (Finck et al., 2019). A popular method, is to use ARX-models based on neural networks (a special case of recurrent neural networks (Pang et al., 2020) for forecasting the solar radiation (Vaz et al., 2016, Ferracuti et al., 2017, Boussaada et al., 2018). These take the previous n observations/states/inputs as input and predicts the next output at time $n + 1$. The performance compared to ARX- and grey box models seems to vary from application to application with no clear victor. A general downside of neural network approaches is the critical dependence on large data sets for training and sensitivity towards non-physical behaviour in regions where data is not present.

5.1.3. Outdoor Air Temperature Forecasting

For predicting the outdoor air temperature, meteorological forecasts (solving lots of coupled Navier-Stokes equations) perform well. For well-insulated buildings, the dynamics of the outdoor air temperature does not significantly influence the indoor air temperature. A building envelope can be thought of as low-pass filter, which filters out the high-frequency variations of the fluctuating outdoor air temperature (Nielsen and Madsen, 2006). For this reason, the need for heating in well-insulated buildings based on the outdoor air temperature is mostly based on the low-pass filtered signal — which may be close to constant. Thus, if no sun is present, the heat required to keep a comfortable indoor temperature during the day is mostly constant.

Many methods for forecasting the ambient air temperature have been used in the literature leaving the modeller with many choices. Dynamical models — like ARMA models — are natural choices for modelling the outdoor air temperature due to their simplicity and easy usage (Murat et al., 2018). Other methods such as neural network models (Papantoniou and Kolokotsa [2016],), regression models, or gradient boosting methods (Ma et al., 2020) are also used for predicting the outdoor air temperature.

5.1 Mean value-based predictive control

By far, the most common type of MPC implemented in buildings is the "simplest" kind of MPC, which is based on the mean value. Often, the models are also formulated as linear models, which often makes the optimal control problem convex, and therefore fast and robust to solve.

The most common objective function in implemented cases is to use the economic price of operating the building, also known as Economic MPC (EMPC). Often, to give the controller room and flexibility to optimise the operations, a certain allowed temperature interval is given:

$$T_{\min} \leq T_k \leq T_{\max}$$

This temperature span may vary in time, e.g. it is often widened during night, since occupants are either asleep in residential buildings or offices and schools are unoccupied. This allows the controllers to lower the temperature during night, or heat up, if the prices (being economic, CO2, etc.) are cheap. The following pages review multiple real-time economic MPC implementations.

5.1.1 Economic MPC

West et al. (2014) discuss MPC in large office building. They consider varying costs in the objective function, (it was however implemented as constant in the demonstration period). Objectives include comfort dissatisfaction using the ASHRAE standards to evaluate satisfaction, greenhouse gas emissions from the heating system, and the economic costs of the heating system. Indoor comfort was evaluated via feedback from occupants; however there was no detailed evaluation of the measured temperatures.

Huang et al. (2015) develop an MPC for control of the indoor air temperature of an airport terminal in Australia. The MPC also utilises an artificial neural network to handle the uncertainties in the HVAC processes. For the thermal model of the air, they use an explicit Euler method with zero-order hold for the input. They do apply a Kalman filter method for updating the states. They both carry out a simulation and an experiment to test the model and MPC, and find savings around 13 percent. They combine economic costs with a 1-norm penalty on the reference tracking term.

Finck et al. (2019) present and implement EMPC for a Dutch building. The models for the building heat dynamics and the weather forecasts are based on artificial neural networks - this has the disadvantage that it requires large amounts of data. They asked the occupants to follow a fixed schedule for being present and opening and closing windows. They tested the controller for flexibility optimisation and to regulate on-site power generation and grid-consumption and feed-in. The objective was purely economic while having constraints on the indoor air temperature.

Liao and Dexter (2004) identify a single-zone model for a three story building, where they model the average room temperature of the entire building. All zones are equally big, so the weighted average is simply the algebraic average. Each floor is similar in terms of the heating equipment (i.e., easy to model).

5.2 Linear quadratic predictive control

Another popular control scheme is based on what is known as linear quadratic controllers (quadratic objective functions with linear models). The optimal control objective is typically on the form:

$$\phi_k = \int_{t_k|}^{t_k+T} \|x(t) - r(t)\|_2^2 + \|u(t)\|_2^2 + g(x(t), u(t))\mathrm{d}t \tag{5.4}$$

where $x(t)$ is the system state, $r(t)$ is a reference signal, $u(t)$ is the input (e.g., heat input), and $g(t)$ is an additional regularisation terms that might appear in the objective. This objective minimises the variance of the system around the reference point. It has useful trade-offs, which can be visualised in so-called Pareto fronts (Fig. 5.1). It illustrates the inherent trade-off from the objective function in Equation. 5.4: If we require a smaller variance of the input signal, it comes with the cost of increasing the variance of the controlled system.

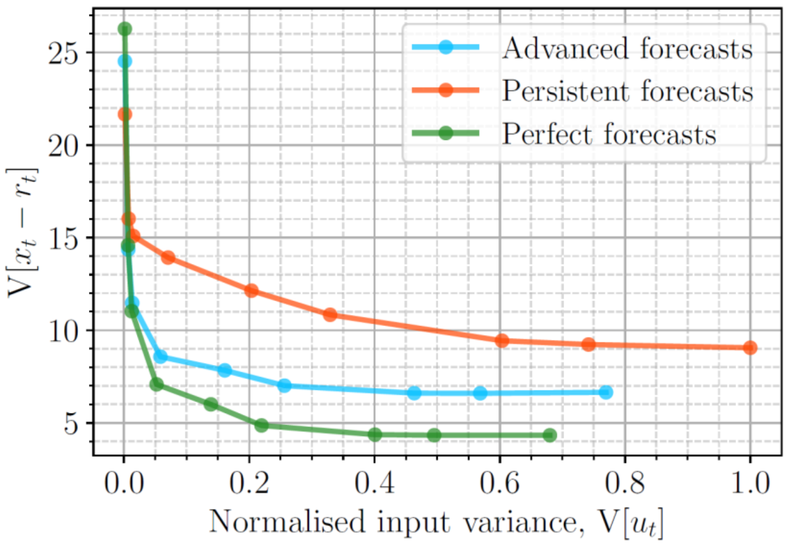

Figure 5-1. Pareto front of the variation of the input and the controlled system around the reference signal.

De Coninck and Helsen (2016) present the results of implementing an MPC in a two-storey office building using a linear GB model. They employ a reference tracking, linear quadratic controller, tracking the optimal comfort level (according to ASHRAE standard), and combines it with a linear economic cost term. Using such a setup still makes the optimal control problem convex. They report cost savings of between 30 and 40 percent while, at the same time, reducing discomfort. They do room temperature averaging since it is not possible to identify a multi-zone model because the heat usage in each room is not known (only on building level). This is a very common issue for many buildings with water-based heating systems (Thilker et al., 2021a). To model the individual rooms, more black-box related models are required such as simple time-series models, e.g. ARX models, or complex neural network models.

Široký et al. (2011) present an experiment with an implemented MPC in a five-floor building block on a university campus. The room temperature was measured in two reference rooms in the building and parameters in a linear RC-model were estimated from data. An MPC was run for two weeks, and energy savings were achieved over a rule-based control; however the room temperatures are not evaluated in detail, and naturally, besides the reference rooms, there is no other information about temperatures in the other rooms. They also combine the quadratic objective function to track a temperature reference set-point and include the economic heating costs.

Moroşan et al. (2010) present a simulation study demonstrating how different MPCs for multi-room temperature control in a building perform. The focus is on the interaction between the rooms in the form of heat exchange due to temperature differences. The results indicate that either a centralized control, which has a full multi-room model, or a distributed control, where the room models exchange information, is preferable over a decentralized control, which does not take the interactions into account. They use a minimum variance reference tracking objective to minimise discomfort in the occupation periods.

5.3 An In-Depth Example

This section gives a practical example of an economic MPC implementation in a Danish school building, where the indoor air temperature is controlled to demonstrate flexibility. For more details of this example, please see Thilker et al., (2022b).

Figure 5.2 shows a photo of the building. It was built in 1929 and thus not insulated according to modern standards. It has three floors and where the uppermost floor is a renovated attic. Heat is supplied by the local district heating network, which is used for space heating, air-handling-unit, and domestic hot water.

Figure 5-2. The Danish school building in which an MPC was installed and controlled the indoor air temperature.

5.3.1 Brief Introduction to the Building and the Problem

The building's space heating is a hydronic water-based heating system. The heat equipment in the rooms consists of radiators. The radiators are controlled by thermostatic valves that use a *set-point* to determine the pin-position and the water flow. Since the rooms are dimensioned differently in terms of size, number of radiators, the number of windows (and their orientation), it is a comprehensive task to compute the heat usage for individual rooms. To simplify the control task, the indoor air temperature in the building is represented by the average temperature of all measured temperatures in the rooms. Furthermore, the controller sends out the same set-point to all rooms.

The thermal model of the building is based on stochastic differential equations, where observations are taken at discrete times t_k

$$\mathrm{d}\boldsymbol{x}(t) = f\big(\boldsymbol{x}(t), u(t), \boldsymbol{d}(t)\big)\mathrm{d}t + g\big(\boldsymbol{x}(t)\big) \tag{5.5a}$$

$$\boldsymbol{y_k} = h\big(\boldsymbol{x}(t_k)\big) + \boldsymbol{v_k}, \quad \boldsymbol{v_k} \sim N(0, R) \tag{5.5b}$$

where:

- $\boldsymbol{x}$, $u(t)$ and $\boldsymbol{d}$ are the system states, controllable inputs and non-controllable inputs respectively.
- f is the deterministic dynamics,
- g is the diffusion function,
- ω is a standard Brownian motion, and
- v_k is the observation noise.

The above model formulation is an example of a grey-box model that includes physical dynamics in f and describes stochastic elements by the Brownian motion that are too complex to model otherwise. Thilker et al. (2021a) modelled the thermal dynamics of a Danish school building in a DH network using a hydronic heating system with thermostatically controlled radiators. Such a model enables an MPC to control the thermal dynamics and perform tasks such as peak shaving or load balancing. They find the following states useful to include in a grey-box model:

- The indoor air temperature, $T_i(t)$. This is typically the variable that is important to maintain a comfortable indoor climate.
- The temperature of the building envelope, $T_w(t)$. This contains important information about the insulation-level and how much heat is stored in the walls.
- The flow of the water in the space heating system, $\Phi(t)$; this varies as the thermostats in the radiators open and closes.
- The temperature of the radiators in the building, $T_h(t)$ is the component that delivers the heat in the rooms.
- The return water temperature, $T_{\mathrm{ret}}(t)$, is important since it determines the amount of heat the building uses.

Together, the above states form a model that is sufficient in describing the important thermal dynamics in a large building in a DHN. The controllable input to the system, $u(t)$ is the set-point to the radiator thermostats in the building. The map between the difference in set-point and room air temperature and how open the valves are was modelled using a sigmoid function. Before the actual implementation, the above model was tested in a simulation framework to investigate and fine-tune the MPC as to obtain the desired thermal behaviour of the building (Thilker et al., 2021b).

The next section briefly introduces the MPC implementation in building.

5.3.2 Implementation of MPC in a Smart Building

On a building level, the MPC has the objective to satisfy certain constraints (e.g., a comfortable indoor air climate at all times) while at the same time minimising some objective. For economic MPC (Kuboth et al., 2019), typically, the objective is to minimise the heating costs while satisfying constraints on the thermal conditions of the building. This section presents a case study where the controller needs to adjust the thermostatic setpoints to regulate the indoor air temperature.

A well-designed MPC is capable of optimising both the thermal comfort of the indoor environment and energy usage (De Coninck and Helsen, 2016). If the building manager wants to help the district heating network lower the supply temperature and decrease peak loads, the cost in the objective function could follow a fictive price signal that reflects the degree to which it is acceptable to heat at any given time in order to achieve a lower peak demand on district-level. The next section shows results from the actual implemented MPC that demonstrates the building's ability to shift its heat demand given a fictive price signal.

To see all the details in the MPC implementation, the reader is referred to Thilker et al. (2021a) and (Thilker et al., 2022b).

5.3.3 Some Control Results from Borgerskolen

Figure 5.3 shows closed-loop results of the implemented MPC in the Danish school building. The upper plot shows the heat price and the building's heat load. The middle plot shows the average indoor air temperature, the temperature constraints, and the sequence of optimal set-points. It is evident that the building is able to shift a significant amount of its heat load in the presented setup while respecting the comfort constraints.

Since the controller uses the average indoor air temperature, variation in the temperature between the rooms is expected. The lower plot shows the individual room air temperatures. The temperatures range between 16 and 26 °C during the experiment. It illustrates that even though the average temperature respects the comfort bounds, almost all rooms violate the constraints at some points.

Some ideas to mitigate the large variance in the rooms could be to learn a set-point offset for each room using feedback from the occupants. Another is to use room-specific models where individual controllers for each room regulate the room air temperature independently from the other rooms. Thilker et al. (2021a) formulate ARX models to describe and predict the room air temperatures. Such models are also readily used for MPC.

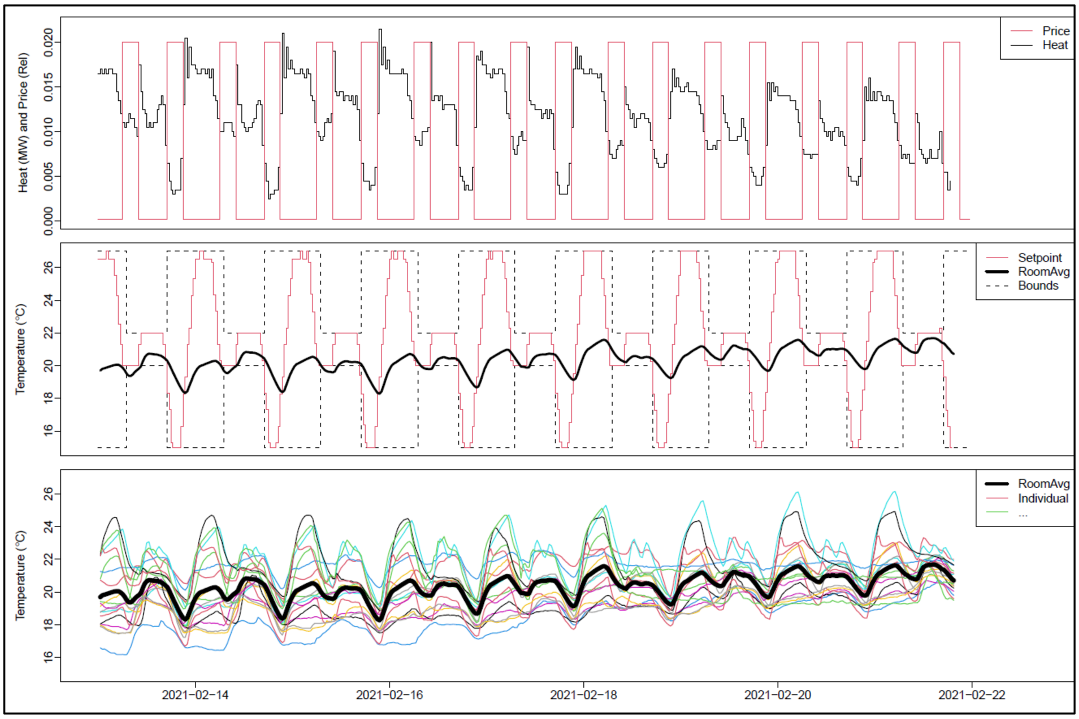

Figure 5-3. Real-life control results of the control experiment carried out in the Danish school building, Borgerskolen. The upper plot shows the heat load on top of the electricity price levels. The middle plot shows the average indoor air temperature together with the temperature bounds and the thermostatic set-point (control input). The lower plot shows the individual room air temperatures and reveals a large spread, which is not visible in the average temperature.

5.4 Hierarchical control for future smart grids

This section describes how the building controllers considered in the previous sections can be considered as the low-level controllers of a multi-level or hierarchical control setup for solving grid or ancillary service problems in future smart energy systems. Briefly speaking we will describe how the physics (dynamical formulations) of the buildings and grids can be linked to the conventional electricity markets which is characterised by bidding and clearing (static formulations). Subsequently, we shall briefly outline how these principles can be generalised to multi-level and hierarchical control problems.

5.4.1 Hierarchical Control for utilising energy flexibility

In this section, it will be explained how to control the demand of smart buildings by generating energy prices such that the building reacts and adapts its consumption accordingly. The basic concept is illustrated by Fig. 5.4, where a smart building, from an external perspective, takes an input (price) and gives and output (demand). Analysed in this way, a model is developed to calculate an index denominated the *Flexibility Function*, which predicts demand as a dynamic function of price. The Flexibility Function could be any dynamic model; it has been proposed as one of the fundamental MIMs (*Minimum Interoperability Mechanisms*) for energy systems (Dognini et al., 2022). In (Junker et al., 2018), a linear model (step-response function model) is suggested. For nonlinear systems it is shown in (Junker et al., 2020) that a grey-box model using a set of non-linear stochastic differential equations might be more appropriate for some systems. In general, the flexibility function should be considered simply as link between price and demand.

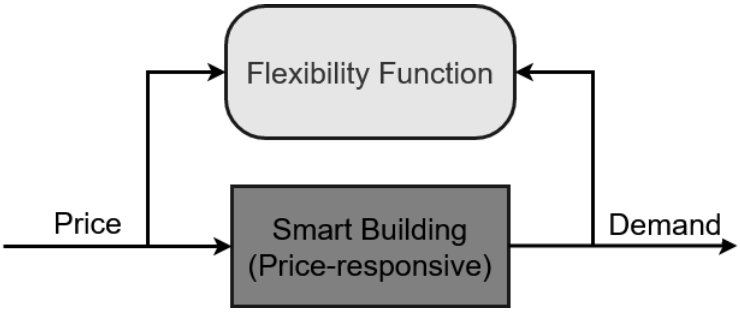

Figure 5-4. The demand of a smart building can be predicted as a function of prices.

Given a Flexibility Function for the building, a second controller can be formulated where the objective is to control the building's demand according to some criteria, and the decision variable is the price (say, electricity price as a function of time). As shown in Figure 5.5, the Flexibility Function can be used to generate prices according to some reference. The reference could be a desired energy consumption in time. Notice how the demand acts as the feedback to the controller, closing the loop.

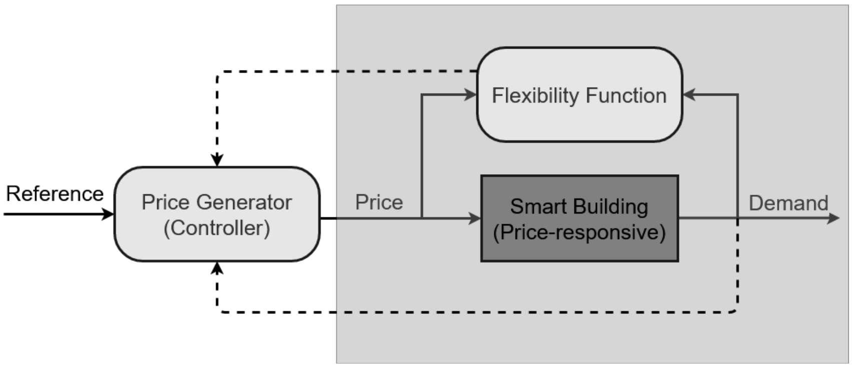

Figure 5-5. Using a Flexibility Function to generate price signals and demand as control feedback.

Let FF be the Flexibility Function that takes energy prices as input and gives the building's expected demand as output, while r_l is a reference load. Then, a simple upper-level optimisation problem can be written as:

$$\min_{C_u} \quad (\mathrm{FF}(C_u) - r_l)^2. \tag{5.6}$$

where C_u is the future energy prices. Obviously, it might be necessary to impose limits on how much the price can change, requirements on the average value, and a more sophisticated optimisation problem than the minimum variance formulation as discussed in Junker (2019). Combining this optimisation problem with the lower-level optimisation problem of the building's heating system, the Flexibility Function couples the two in an elegant fashion:

$$\begin{array}{lll} \min\limits_{C_u} & (\mathrm{FF}(C_u) - r_l)^2 & \text{Upper level} \\ \hline \min\limits_{u_k} & \sum\limits_k {C_u}^\top u_k & \text{Lower level} \\ s.t. & \mathrm{d}x = f(x,u,d,t)\mathrm{d}t + g(x,t)\mathrm{d}\omega & \end{array}$$

where, in this case, the lower optimization problem is formulated as an economic MPC problem. As mentioned above, the Flexibility function is considered to be one of the fundamental MIMs (Minimum Interoperability Mechanisms) for energy systems since it is instrumental for the coupling between the building level and upper level representing the grids and aggregators.

Notice how the two optimisation problems are solved independently from each other, thus preserving autonomy and privacy for the building owners while simultaneously allowing an aggregator to utilise the energy flexibility. In practice, there are going to be a lot of smart buildings for each aggregator that all have independent control problems and preferences. This method scales well to this case since the computational burden for the upper-level remains constant — with the Flexibility Function simply representing the aggregated response from the smart buildings (Junker, 2019).

5.4.2 Multi-level control and markets

Ultimately the purpose of the future smart energy system is to establish a connection between the controllers operating at local scales, and high-level markets operating at large scales. This includes coupling sectors and establishing dynamic markets to reflect an increasingly dynamic supply and demand of energy. Essentially a spectrum of all relevant spatial aggregation levels (building, district, city, region, country, etc) has to be considered. At the same time, the established markets must ensure that all power systems (on all temporal and spatial scales) are balanced. Consequently, data-intelligent solutions for operating flexible electrical energy systems have to be implemented on all spatial and temporal scales.

To address these increasingly important issues, several solutions have been proposed in recent years. Some significant solutions are Transactive Energy, Peer-to-Peer, and Control-Based solutions, as described in [De Zotti et al., 2018a].

Traditionally, power systems are operated by sending bids to a market. However, in order to balance the systems on all relevant horizons, several temporal-specific markets are needed. Examples are day-ahead, intra-day, balancing and regulation markets. The bids are typically static and consisting of a volume and duration.

Given all the bids, the so-called supply and demand curve for all the operated horizons can be found. Mathematically, these supply and demand curves are static and deterministic. Merit order dispatch is then used to optimise the cost of generation. However, if the production is from wind or solar power, then the supply curve must be stochastic, and the demand flexibility has to be described dynamically— e.g., by the introduced Flexibility Function. Consequently, it is believed that it is necessary to introduce new digitised markets, which are dynamic and stochastic. And instead of using a large number of markets for different purposes (frequency, voltage, congestion, etc.) and on different horizons, we will suggest using concepts based on the Flexibility Function and stochastic control theory; exactly as described in the previous section for the two-level case. We call this a Smart-Energy Operating-System (SE-OS) (Madsen et al., 2015, 2016, Madina et al., 2019).

If we zoom out in space and time, i.e. consider the load in a very large area on a horizon of days, or maybe the next day, then both the dynamics and stochasticity start to matter less (and may even be more or less eliminated); hence, we can use conventional market principles, as illustrated in Figure 5.6. If we zoom in on higher temporal and spatial resolutions (e.g., a house), the dynamics and stochasticity become important, and consequently we will suggest using the control-based methods for the flexibility as discussed in this chapter. This implies that in real-time the link is handled simply by a one-way communication or broadcasting of a price-signal.

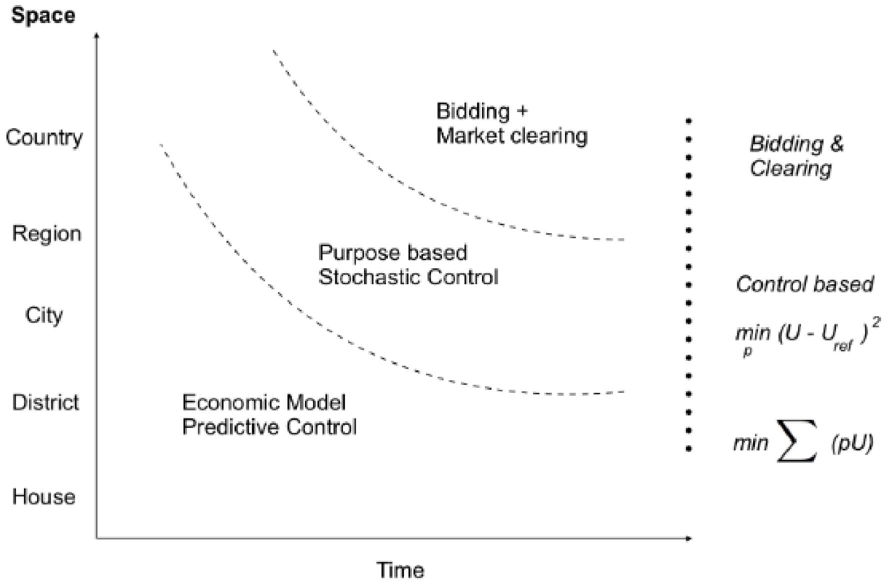

Figure 5-6. Hierarchical control and markets.

All these principles for forecasting, control and optimisation are included in the so-called Smart-Energy Operating-System (SE-OS), which is used to develop, implement, and test solutions (layers: data, models, optimisation, control, communication) for operating flexible electrical energy systems at all scales. See (Madsen et al., 2015, 2016, Madina et al., 2019, De Zotti et al., 2018b) for further information.

The simplicity of broadcasting price signals for activating demand-response needed e.g., for a distribution system operator, implies that basically all appliances can contribute to unlocking the needed flexibility at the relevant spatial and temporal coordinates. At the same time, the end-user can easily set up local preferences in their Home Energy Management Systems (HEMS) in a weighted combination of a focus on e.g., comfort, costs, emission and energy efficiency. The overall simplicity of the concepts ensures fast adaptation and stimulates an effective scale up of the use of flexibility and demand response technologies in the market.

Basically, the setup decomposes the computation effort in several computations at many levels of the hierarchy. Similarly, the Home Management Information Systems (HMIS) can be used to provide information about the aggregated flexibility which can be offered from a particular building, and for energy communities similar aggregation principles apply.

In conclusion, the Smart Energy OS principle is using the Flexibility Function as one the fundamental MIMs to ensure a minimal but sufficient interoperability on all relevant levels, and for many appliances low-cost solutions can be established using mobile phones and similar edge computing technologies. Data is typically kept at the edge (the building level), and computations carried out, in a coherent hierarchy consisting of edge, fog and cloud levels with privacy, transparency and fairness in mind.

Regarding data management, security and privacy aspects we refer to the Annex 81 Report *A Data Sharing Guideline for Buildings and HVAC Systems* (White et al., 2023) for comprehensive discussions and guidance.

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6. Data-Driven Fault Detection and Diagnosis

- Data-driven FDD process.
- Insights into applying data-driven FDD in various building subsystems and the whole building.
- Common data sources for the development of data-driven FDD.
- Important metrics for evaluating data-driven FDD methods.
- Future opportunities to advance data-driven FDD.

6.0 Introduction

Building systems, including heating, ventilation and air conditioning (HVAC) systems, are usually subject to faults that can lead to undesirable performance, such as excessive energy waste, high maintenance costs, uncomfortable indoor thermal environments, and poor air quality. These faults are the result of sensor failure, equipment failure, or faulty system operation. Studies have shown that 15%-30% of energy may be wasted due to building system faults and improper controls (Katipamula & Brambley, 2005). Therefore, fault detection and diagnostics (FDD) or automated fault detection and diagnostics (AFDD) as it is also commonly referred to, is crucial to ensure reliable system operation and avoid energy waste. It is reported that FDD users in the office and higher education market sectors of the United States were able to achieve 10% median energy savings annually with two-year simple payback period (Kramer et al., 2020). It demonstrates the high competitiveness of FDD systems as a profitable investment option in the building sector.

Over the past decades, many FDD methods have been developed. With the advancement of data science and the wide adoption of building automation systems (BAS) or other smart building technologies, data-driven FDD is gaining increased attention. Compared to the traditional expert knowledge/rule-based approaches that are typically seen in commercial-off-the-shelf FDD products, data-driven FDD requires little or no *a priori* knowledge and has the potential to achieve high detection and diagnostic accuracy at relatively low cost (Hu et al., 2021a).

Despite the promise of data-driven FDD, the market has been slow to adopt it (Granderson et al., 2017; Wall & Guo, 2018). This chapter aims to advance the development and market adoption of data-driven FDD by providing a survey of the state-of-the-art technologies from three main aspects: process (Section 6.2), systems studied (Section 6.3), and evaluation metrics (Section 6.4). Section 6.5 discusses challenges and opportunities for future advancement of data-driven FDD. Section 6.6 concludes the chapter. A more detailed review of the state-of-the-art technologies can be found in (Z. Chen et al., 2023).

6.1 Main Steps of Data-driven FDD Process

Based on the literature, a data-driven FDD process can be summarized as shown in Figure 6.1. Methods used in each FDD step are discussed in the following subsections.

6.1.1 Data Collection

Collecting data from a BAS is often the most time-consuming and labor-intensive process due to the fact that individual buildings have unique BAS configurations, database structures, and datapoint naming conventions (Pradhan et al., 2022). The use of standardized communication protocols, e.g., Building Automation and Control Network (BACnet), and metadata schemas, e.g., Project Haystack, Brick, and the recent ASHRAE 223p standard (Pritoni et al., 2021), can effectively ease the data collection process. Nevertheless, FDD applications that utilize metadata or semantic graph are still very few and underdeveloped (Ploennigs et al., 2017).

6.1.2 Data Cleansing

Often, datasets obtained from the BAS or other sources may be incomplete due to sensor and equipment failures, communication or transmission issues, data corruption, or inconsistencies due to sensor noise, thus, leading to loss of valuable information (Pritoni et al., 2018). These issues exist in almost all kinds of sensors/automation systems and can significantly affect the FDD outcomes since most data analysis and statistical tools are not designed to handle incomplete data. Existing literature on data imputation methods for building data has focused on univariate time series data using statistical methods (Ouyang et al., 2017), nonlinear machine learning, and deep learning (Pradhan et al., 2022; J. Yang et al., 2019). Ensemble methods, which utilize multiple imputation methods for improved missing value prediction, have also been developed recently (Zhang, 2020). While most of the techniques reported for missing data imputation are focused on generic data-driven applications, there are few studies addressing the missing data issue for FDD purposes, such as (D. Li et al., 2019) .

6.1.3 Data Preprocessing

Data used for training FDD algorithms often need to be preprocessed beforehand to achieve desired training performance. This step may include feature selection, data reduction, data scaling, data transformation, data partitioning, etc (Fan et al., 2021). Typically, this step is performed offline (e.g., selecting some relevant features from historical data), and then the results of the pre-processing (e.g., the selected features), are applied to the snapshot data. This section mainly reviews the feature selection techniques that are often used to find the key inputs for a data-driven model used for the FDD process. Using only selected features instead of the entire dataset reduces the model complexity and model overfitting issues.

Various feature selection methods, such as filter, wrapper, embedded, and hybrid methods, have been reported for FDD applications (Chandrashekar & Sahin, 2014). Filter methods, like the information greedy feature filter (IGFF) developed by (X. Li et al., 2021), are computationally fast and less prone to overfitting. However, they may not always find the feature subset with the highest model accuracy (Zhang & Wen, 2019). Wrapper methods, which train and evaluate specific models with different feature combinations, are computationally expensive and susceptible to overfitting (Zhang et al., 2020). Embedded methods that combine both the filter and wrapper methods are usually incorporated into a specific learning algorithm such as decision trees (DT) and random forest (RF) (R. Yan et al., 2016). Embedded methods that are not incorporated into the learning are categorized as hybrid methods, such as (Han, Gu, Hong, et al., 2011; Han, Gu, Kang, et al., 2011).

Recently, feature extraction methods directed at identifying and extracting interesting "localized" patterns within a timeseries to guide the feature selection process have also gained attention (Zhang et al., 2020).

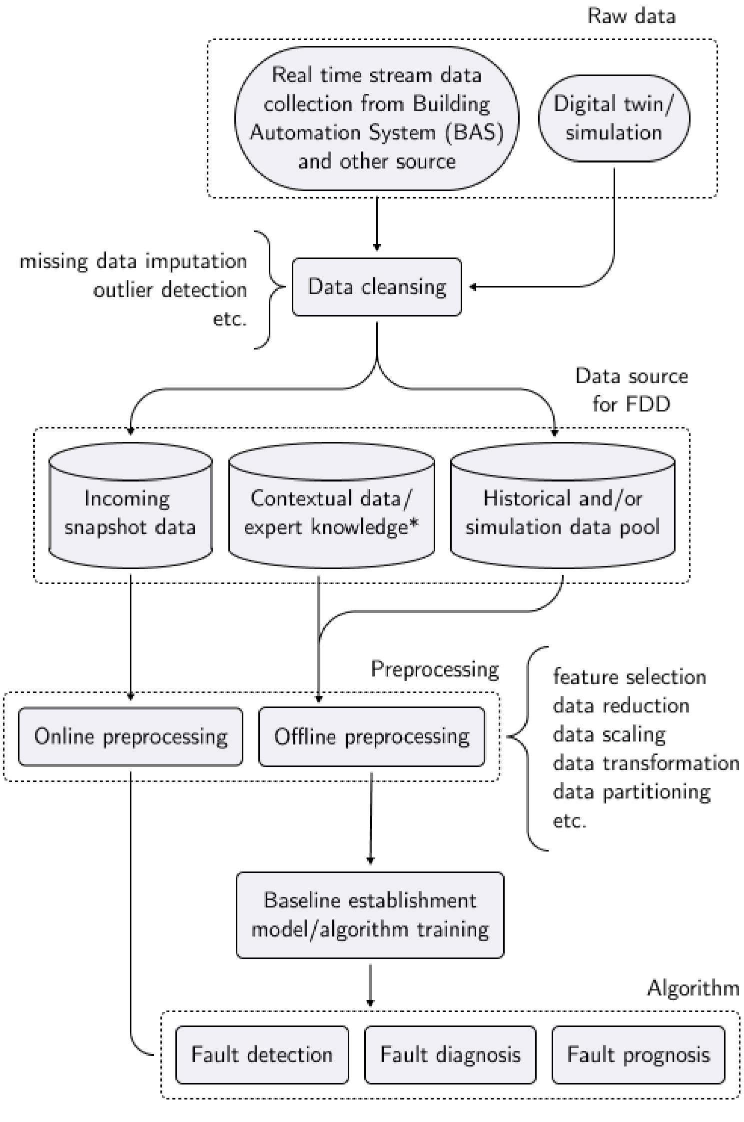

Figure 6.1: A General Data-driven FDD Process.

6.1.4 Baseline Establishment

To enable FDD, a baseline representing normal system operation is often required. A true fault-free status is rarely achievable for real buildings; therefore, fault detection typically identifies when a building's status significantly differs from its baseline (Y. Chen et al., 2021). Baselines can be generated by simulation (Miyata et al., 2020) or constructed from historical data.

HVAC systems exhibit different dynamics under various operation modes (heating, cooling, etc.), and it is challenging to differentiate variations caused by weather and/or internal conditions from abnormalities triggered by faults (Y. Chen, Wen, & Lo, 2022). Most data-driven FDD methods compare real-time operation data with the baseline, necessitating that the operation mode of the baseline matches that of the incoming snapshot data. Existing studies focus on pattern recognition and motif discovery strategies to construct a baseline that accounts for outdoor weather conditions, daily internal load profiles, and temporal association rules (Huang et al., 2021; Lin & Claridge, 2015; Piscitelli et al., 2020). A baseline model should ideally incorporate and learn changes influenced by specific control strategies implemented, rather than detecting them as faults.

6.1.5 Fault Detection

Data-driven fault detection strategies have shown promise in efficiently characterizing HVAC system operations and developing accurate, scalable models while reducing engineering time and labor cost. Fault detection methods can be categorized as supervised, semi-supervised, or unsupervised ((Mirnaghi & Haghighat, 2020; Zhao et al., 2019).

Supervised methods require both normal operation and labeled fault data. Supervised methods can be further categorized into classification methods or regression methods based on the type of model output. While classification methods such as SVM (Madhikermi et al., 2019; Montazeri & Kargar, 2020) and DT (Capozzoli et al., 2018; Piscitelli et al., 2020)are used to predict whether the incoming data belongs to the fault or fault-free class, regression methods such as support vector regressions (SVR) (J. Liu et al., 2018; Zhao et al., 2013) and neural networks (NN) (Du et al., 2014; Miyata et al., 2020; Sipple, 2020) typically predict continuous variables, representing the system operation status, which is then compared with the baseline to identify any occurring faults. Both types of supervised methods have been widely used for fault detection in building HVAC systems. However, the challenge with supervised methods is in obtaining sufficient labeled fault data for training the models, often leading to imbalanced classes. Given the difficulty and the cost to label data, models used by supervised methods are often trained using data collected from older components or simulation models which can lead to lower detection accuracy and higher false alarm rates.

Semi-supervised methods are suitable when limited labeled fault data is available. Semi-supervised methods transfer unlabeled data into labeled classes by comparing the incoming data with normal operation, and updating the training set iteratively (K. Yan, Chong, et al., 2020). Although semi-supervised methods perform better when limited labeled fault data is available, semi-supervised methods have a higher computational cost than supervised learning (Mirnaghi & Haghighat, 2020).

Unsupervised methods do not require fault labels and are useful for discovering hidden correlations and fault impact analysis. Some of the popular methods in this category are clustering algorithms (Cheng et al., 2016; Du et al., 2014; Fan et al., 2015; Gunay & Shi, 2020) and principal component analysis (PCA) (Montazeri (Y. Chen et al., 2021; Y. Chen, Wen, & Lo, 2022; Montazeri & Kargar, 2020) which are used typically with pattern recognition and motif discovery methods. Since only fault-free data is required for deploying unsupervised methods, these methods are easier to develop and deploy for fault detection purposes.

6.1.6 Fault Diagnosis

Identifying or localizing the root cause of a fault or anomaly is typically more challenging than detecting the anomaly, since different faults (e.g., malfunctioning hardware, software errors) can lead to the same symptom. Correctly diagnosing the root cause of a fault often requires a detailed knowledge of the HVAC configuration and control strategies, both of which are specific to a building. Bayesian network (BN) models based on the conditional probability theorem that predicts the fault beliefs based on a set of observations are popular (Lampis & Andrews, 2009). BN models can incorporate the system structure information through probabilistic conditional relations between faults and their symptoms. These probabilities can be updated after new observations (evidence) of the system are obtained. Further, by adding uncertainty factors for reasoning, the BN model can avoid incorrect diagnosis by avoiding under-responsiveness or over-responsiveness to evidence (Zhao et al., 2017). Successful implementation of BNs for both component-level and system-level fault diagnosis has been demonstrated in the existing literature, such as (Zhao et al., 2015, 2017) for AHUs, (Xiao et al., 2014) for VAV terminal units, and (Verbert et al., 2017) for system-level HVAC faults with interdependencies between components.

More recently, (Y. Chen, Wen, Pradhan, et al., 2022) developed a discrete BN-based method for cross-level faults diagnosis in commercial buildings. Unlike continuous BNs which use continuous probability distributions in each node of the network, the continuous variables are discretized to represent fuzzy events in a discrete BN ((İçen & Ersel, 2019). This makes modeling the BN parameters easier and more efficient, especially when obtaining parameters from expert knowledge and incomplete field data (Rohmer, 2020).

Alternatively, dynamic BN models that describe the temporal relationship of the fault states within each time slice have shown to be effective for fault diagnosis as well. By carrying past information, a dynamic BN allows fault beliefs to accumulate over time, thus helps eliminate measurement errors and improve diagnosis accuracy (Zio & Peloni, 2011).

Other diagnostic inference methods such as fault-trees that are based on a decision tree and multiple binaries of if-statements are usually time-consuming and may be highly dependent on domain expertise (Mirnaghi & Haghighat, 2020). Alternatively, classification methods such as SVMs (Lee et al., 2021)and ANNs (Du et al., 2014; Miyata et al., 2020) are also popular. These methods generally require a large amount of labeled data for model training. Additionally, the inference process behind the diagnosis of such black-box models lacks transparency and interpretability (G. Li et al., 2021; T. Li et al., 2021).

6.1.7 Fault Prognosis

Fault identification and diagnosis through FDD may not always be sufficient, as some faults in building HVAC systems occur gradually, leading to excess operation and maintenance cost (C. Zhong et al., 2019), and energy waste (Mirnaghi & Haghighat, 2020) over time. It is estimated that over 20% of HVAC systems are running under early stage of gradual faults resulting over 15% in energy waste (Yu et al., 2014). Therefore, data-driven fault prognosis, which refers to identifying impending faults ahead of time and estimating how soon a fault may occur by analyzing historical or real-time measurements for predictive maintenance and repair schedules, is essential for ensuring the safety, stability and for increasing the lifespan of HVAC systems.

Data-driven fault prognosis methods have been gaining attention in various industries (K. Zhong et al., 2019), but their development for HVAC systems is still in its infancy. Notable applications include time-to-failure for chillers and boilers (C. Yang et al., 2020), motor failure analysis (Ahmad & Atta, 2014), remaining useful life of heat exchangers (Wang et al., 2015), and efficiently predicting the lifespan of AHUs and their components (Y. Yan et al., 2017).

Building on the success of data-driven models in other industrial sectors, techniques such as Recurrent Neural Networks (RNNs) have shown promise for fault prognosis by exploiting temporal correlations in the data (Wu et al., 2020). In addition to RNNs, other approaches like Autoencoders (AE) (He et al., 2021) and Restricted Boltzmann Machines (RBM) (Niu et al., 2021) have also been applied in recent data-driven models for fault prognosis, highlighting their potential for building HVAC systems.

6.2 Systems Studied with Data-driven FDD

Data-driven FDD methods have been reported to be applied to many HVAC components and subsystems for various types of faults. This section summarizes (1) the systems that data-driven FDD have been applied to; (2) the identified faults associated with the systems; and (3) the main data source utilized when developing and evaluating a data-driven FDD method.

6.2.1 Faulty Systems and Identified Faults

HVAC faults can be categorized as hardware and software faults by the types of components. Hardware faults further include equipment faults, sensor faults, and controlled device (including actuator) faults. Software faults further include controller faults (e.g., unstable control), human faults (operator faults) and control logic errors. Figure 6.2 illustrates the workflow of these categories. Reviews on the impact of faults in each category are out of the scope of this chapter.

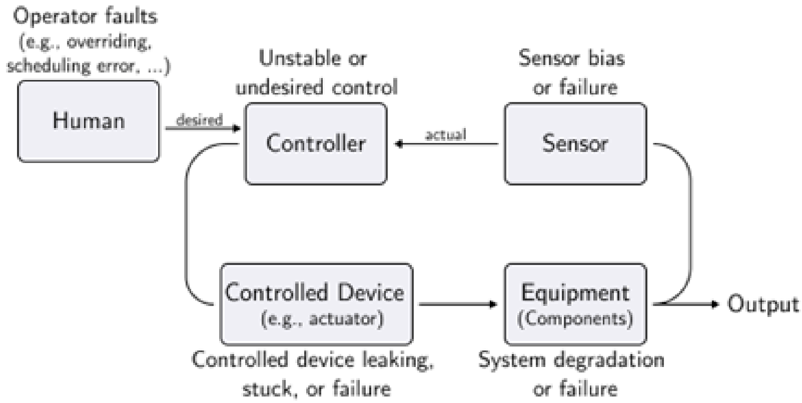

Figure 6.2: Fault distribution in a HVAC system (expanded from (Yu et al., 2014)).

Fault detection and diagnostics can be implemented at the building level, system/subsystem level (e.g., an air handle unit), and/or component level (e.g., a damper) (Wen et al., 2019). Building-level FDD aims to detect and diagnose the occurrence of non-optimal operational patterns by identifying anomalous energy trends in the building energy consumption time series (Capozzoli et al., 2018). At this scale, classification, regression, and pattern recognition techniques are employed to estimate the baseline for the detection of anomalies while sub-meter load data are used to infer the root cause of anomalies at whole-building level (Chiosa et al., 2021, 2022).

For large size buildings, FDD is often applied to AHU-VAV systems, fan coil units (FCU), chillers, and boilers, etc. Yet for small and medium sized buildings, FDD is usually applied to heat pumps and window air conditioners. From the reviewed papers, the most popular research subjects are secondary AHU-VAV systems (35%) and chillers (32%), followed by whole-building studies (17%) and VRFs (7%). The top two faulty systems (i.e., secondary systems and vapor compression systems) and the corresponding classification of the faults in these systems are illustrated in Figure 6.3.

Although most of the literature on FDD focuses on the system/component level, FDD at whole-building level has increasingly attracted the interest of researchers, as it involves complex interactions between building dynamics, external climatic conditions, system operating schedules, and occupant comfort. The main objectives of building-scale FDD include recognizing typical energy consumption patterns, detecting anomalies, and diagnosing these anomalies at the sub-load level. Expert domain knowledge is crucial for achieving these objectives. However, due to the lack of ground-truth datasets, unsupervised learning and pattern recognition techniques are the most commonly employed approaches for whole-building level FDD applications (Y. Chen et al., 2021; Y. Chen, Wen, & Lo, 2022; Y. Chen, Wen, Pradhan, et al., 2022).

6.2.2 Data Source

For data-driven FDD method development, labeled normal and fault data are needed for training and method evaluation purposes. Among the papers reviewed, 48% use lab experiment data, 32% use real building data, and 20% use simulation data. The coupling between the data source and the system type is further shown in Figure 6.4.

Lab experiment data were most adopted. They had been applied in tree-structured learning FDD of chillers (D. Li et al., 2016), GAN-based FDD of AHUs (K. Yan, Huang, et al., 2020), deep learning-based FDD of VRF systems (Guo et al., 2018) and so on. However, there are limited examples of publicly available datasets that have verified ground-truth information on the presence and absence of faults. Four research projects offer valuable publicly available experimental data. The first two are ASHRAE Project 1043-RP data

(Comstock & Braun, 1999) and ASHRAE Project 1312-RP data (Wen & Li, 2012), which have been widely used in chiller and AHU FDD studies, respectively. The third is the building fault detection data to aid diagnostic algorithm creation and performance testing (Granderson et al., 2020), which includes two experimental test datasets for a single-zone AHU-CAV and a single-zone AHU-VAV serving a real building zone, respectively. The fourth is the LBNL fault detection and diagnostics datasets (Granderson et al., 2022), which includes an RTU experimental test dataset.

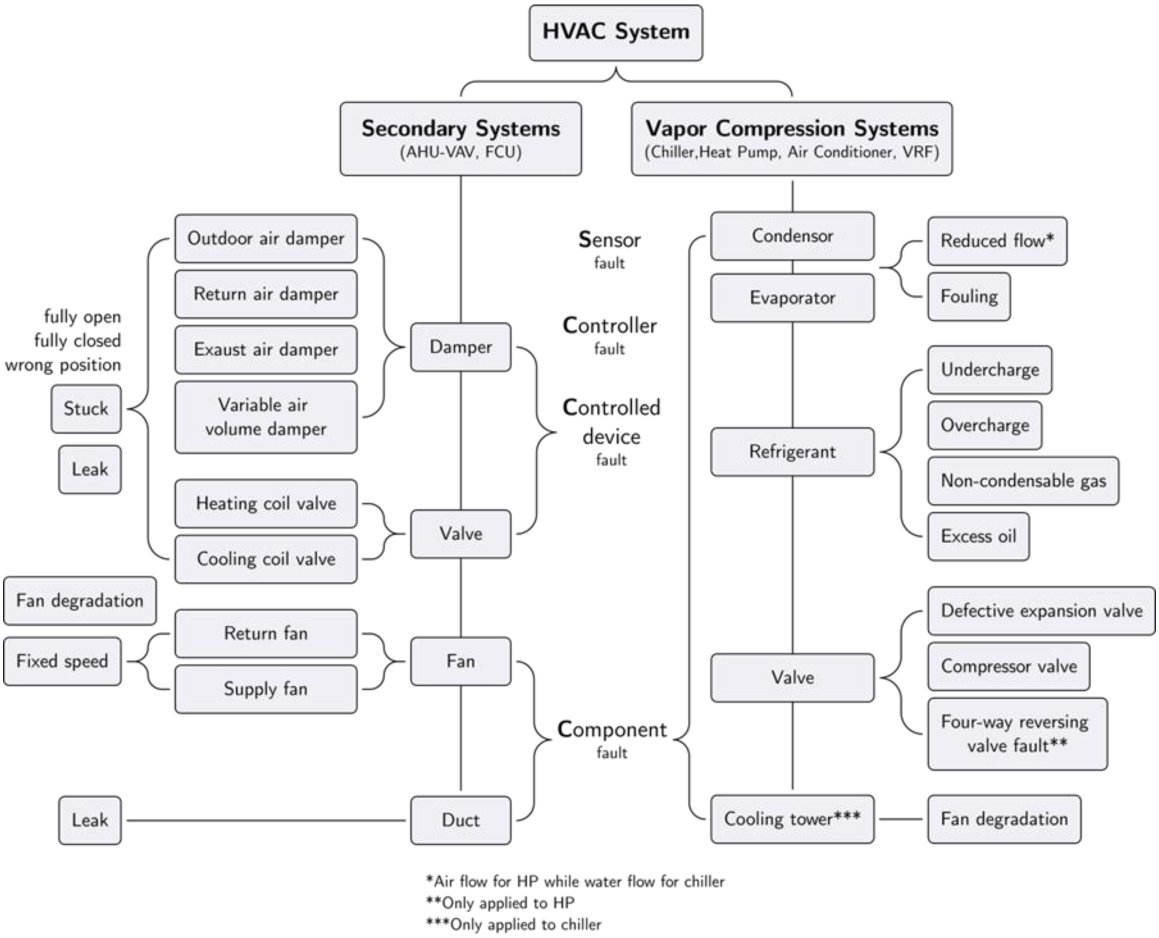

Figure 6.3: Fault classification of HVAC systems.

Simulated data from non-proprietary physical model-based simulation software has been utilized in various studies. Examples include (Du et al., 2014) using a TRNSYS-based simulation testbed for validating a neural networks algorithm for AHU anomalies, (Montazeri & Kargar, 2020) using HVACSIM+ software for SVM and PCA FDD methods, and (Lu et al., 2021) conducting a comprehensive fault impact analysis using a Modelica-based framework. Since these simulation software are designed for fault-free operations, fault generators or similar means are needed to simulate faulty operations, which can sometimes result in unexpected numerical difficulties, such as long simulation times, inaccurate results, or crashing of the simulation program. Therefore, when modeling faults, it is important to avoid some common causes of numerical difficulties, such as numbers that are beyond the computer precision (Z. Chen, 2019) and discontinuous functions (Z. Chen et al., 2021). When modeling faults for large-scale systems, advanced numerical solvers, such as (Z. Chen et al., 2022), that are both efficient and robust shall be considered. In terms of open-sourced simulation datasets, LBNL FDD datasets (Granderson et al., 2022) include large simulated datasets with verified information on the presence and severity of faults spanning seven HVAC systems and configurations: a single-duct AHU, a RTU, a dual-duct AHU, two VAV boxes, a fan coil unit, a chiller plant, and a boiler plant. HVAC-SIM+ and Modelica-EnergyPlus co-simulation were employed to carry out simulations of more than 250 faulted or fault-free condition states (e.g., mechanical faults, control sequence faults, sensor faults, etc.) over a full year of operation.

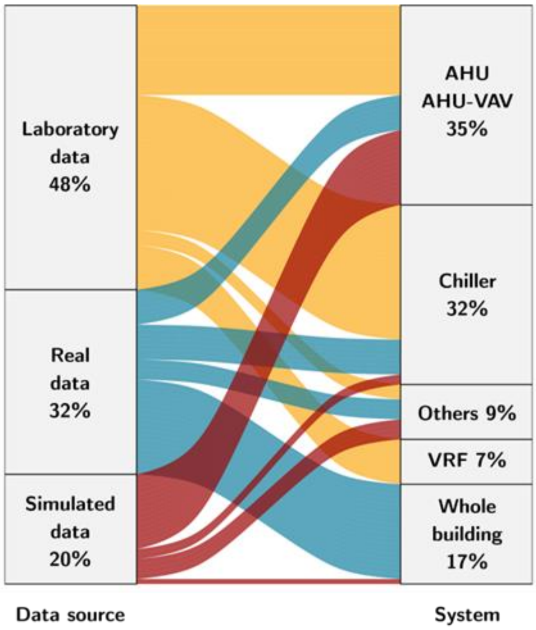

Figure 6.4: Alluvial plot for the reviewed literature classified by data source and system type.

Although 32% of the reviewed studies use real building data, half of the studies focus on the detection of energy anomalies that only require energy consumption data. Publicly available power consumption datasets that can be used to validate anomaly detection algorithms are rare. The competition “Power Laws: Detecting Anomalies in Usage” offers a few datasets with hand-labeled anomalies corresponding to different types of building sites from different geographies (https://www.drivendata.org/). LBNL FDD datasets (Granderson et al., 2020) also include months of field measured RTU data for a compressor control fault and a refrigerant undercharging fault. Obtaining field measurements with labeled faulty operation data is challenging due to the need for manual investigation or maintenance records. Therefore, proper documentation of system changes is crucial to differentiate between normal and faulty operations. In the reviewed studies, real building operation data has been used to detect AHU faults (Gunay & Shi, 2020), chiller faults (Lee et al., 2021), whole-building level faults (Y. Chen et al., 2021; Y. Chen, Wen, & Lo, 2022) and so on.

In addition to the labeled time-series system operation or energy use data under normal and fault conditions, other data sources have also been utilized to support the data-driven FDD algorithms. For example, expert knowledge, maintenance records, building information models (BIM), and real-time occupancy data. Expert knowledge has been integrated into data-driven FDD approaches to (1) detect outliers in the data preprocessing step (Fan et al., 2015), (2) develop, select, and interpret the characteristic features of faults (Verbert et al., 2017; Xue et al., 2017), and (3) support the selection of layers, nodes, and parameters in the BN-based or tree-structured FDD algorithms (Y. Chen, Wen, Pradhan, et al., 2022; D. Li et al., 2016). Maintenance records were utilized to label the ground truth of field measurements, i.e., whether the collected data contain faults or not (Lee et al., 2021; Taal et al., 2018). The BIM was integrated into model-based FDD to provide building design information (e.g., architecture geometry and building equipment information) (Dong et al., 2014). Real-time building occupancy data from internet of things sensors were employed as an additional data stream to detect the degraded building operation performance (Cheng et al., 2016) .

6.3 Evaluation Metrics for Data-driven FDD

It is critical to evaluate and quantify the performance and effectiveness of data-driven FDD methods by using dedicated metrics. Commonly used metrics for evaluating a data-driven FDD are discussed in this section.

6.3.1 General Evaluation Metrics

(Lin et al., 2020) summarized the evaluation metrics for general FDD applications. To assess the performance of a fault detection problem, the evaluation metrics include the true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), false negative rate (FNR), and no detection rate (NDR). To assess a fault diagnosis method, the evaluation metrics often include the correct diagnosis rate (CDR), the misdiagnosis rate (MDR), and the no diagnosis rate (NDgR). Figure 6.5 visualizes the definition of these metrics in a confusion matrix, which will be further discussed in the section below.

6.3.2 Classification Problem Metrics

An FDD problem is essentially a classification problem; fault detection is a binary classification problem, while fault diagnosis is a multi-class classification problem. The general metrics described above are often combined visually or quantitatively into a classification problem metric for a more in-depth evaluation of data-driven classifiers. These classification problem metrics include confusion matrix, accuracy of correct predictions, F-measure (or F-score), Receiver Operator Characteristic (ROC), and Area Under the Curve (AUC).

Confusion Matrix. A confusion matrix is a visualization of prediction results for a classification model (Deng et al., 2016). It depicts the degree of algorithm confusion within different classes and is independent of a concrete classification algorithm (Han et al., 2020). Each matrix element represents the test observations, with the actual (true) class in rows and the predicted class in columns. The diagonal elements show the correct predictions while the off-diagonal elements show the incorrect predictions and how they were misclassified.

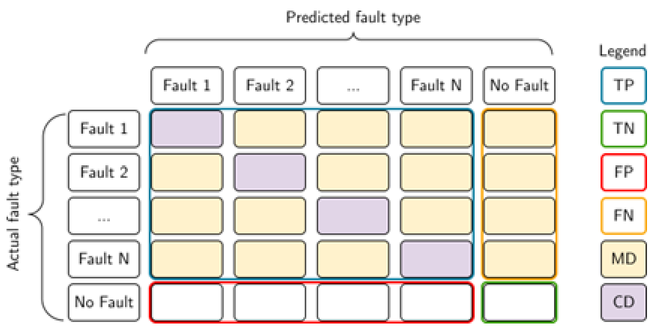

Figure 6.5: Example of a confusion matrix. Given the predictive fault types on the columns and the actual fault types on the rows, the matrix shows the correct diagnosis (CD), misdiagnosis (MD), true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

Accuracy of Correct Predictions. The overall accuracy of correct predictions is defined as the number of correct predictions (i.e., the diagonal elements of the confusion matrix) divided by the total number of observations, as shown in Equation (6.1). This is a simple and intuitive measure, yet it may fail on classification problems with a skewed class distribution.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6.1}$$

F-Measure. F-measure (Pillai et al., 2012) is a comprehensive performance metric to evaluate the quality of a classifier which considers the class-specific performance, as shown in Equation (6.2). F-measure ranges from 0 to 1. The larger the F-measure is, the better the comprehensive performance of the classification model is. In the equation, "Precision" refers to the proportion of correctly diagnosed samples in all positive samples, while "Recall" refers to the proportion of correctly diagnosed samples in the true samples.

$$\text{F} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6.2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6.3}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6.4}$$

ROC and AUC. The ROC curve is a graph showing the performance of a classification model at all classification thresholds (McClish, 1989) which plots two parameters: TPR and FPR. AUC measures the entire two-dimensional area underneath the entire ROC curve from (0,0) to (1,1). A higher AUC indicates that the model performs better in distinguishing between positive and negative classes. (Sipple, 2020) used AUC to compare the anomaly detection performance of various models on predicting failures of HVAC equipment.

6.3.3 Statistical Significance Tests

Statistical significance (or hypothesis) tests can aid in comparing the performance of different classification models. The purpose of statistical significance testing is to help gather evidence of the extent to which the results returned by the evaluation metrics are representative of the general behavior of the classifiers. However, it is noted that significance testing never constitutes a proof that the observation is valid. It provides added support for the observations. The frequently used significance tests, for data-driven FDD, include the t-test (Kim, 2015), McNemar's Test (Lachenbruch, 2014), Wilcoxon's signed-Rank Test (Woolson, 2007), Friedman Test (Friedman, 1937), Nemenyi Test (Nemenyi, 1963), etc. For example, (Han et al., 2020) used Friedman Test and Nemenyi Test to evaluate the performance of different classification models on diagnosing the chiller faults.

6.4 Future Challenges and Opportunities

Although research on data-driven FDD has made great advancements in recent years as discussed above, its broad market adoption remains limited. In this section, we discuss some of the ongoing efforts and challenges to further the development and market adoption of data-driven FDD.

6.4.1 Real-building Deployment

Although much research has been conducted to develop and implement data-driven FDD methods for building systems, most of the studies developed or validated their data-driven methods in simulated environments, in laboratory settings, or using small-scale HVAC systems. Online and real-time implementations of data-driven FDD methods in large-scale systems in real buildings, that can demonstrate the method's performances under various weather conditions, are still rare and in its infancy stage. Reliable, fast and computationally affordable solutions that are readily deployable in the field have not been explored sufficiently (Mirnaghi & Haghighat, 2020). Real building deployments are challenging due to incomplete information and uncertainty (Zhao et al., 2019). The main factors contributing to this challenge are lack of sensors, poor sensor accuracy, imbalance of fault and fault-free training data, ad-hoc naming conventions for data points, non-standardized sensor installation and control logic, and missing data (Zhao et al., 2019). A recent study has shown that data uncertainty has a significant impact on the performance of SVM algorithms for chiller fault diagnosis (X. Li et al., 2021). Validation of data-driven FDD in terms of not only accuracy but also decision-making with real-world uncertainty is needed to overcome market barriers.

6.4.2 Performance Evaluation, Benchmarking, and Fault Impact Analysis

In the literature, there are limited studies that compare the performance between FDD methods, especially under different categories (e.g., data-driven vs rule-based, supervised vs unsupervised). More comparison studies are needed to demonstrate the performance of and identify the weakness of data-driven methods. On the other hand, establishing common FDD datasets with validated ground-truth is needed to facilitate the assessment of different FDD methods. LBNL has released large FDD datasets, including experimental, simulated, and real building data, to support this effort (Granderson et al., 2022).

In building HVAC systems, there are faults that generate relevant effects while others have negligible symptoms. However, the performance evaluation process of a FDD method is mostly based on the calculation of classification accuracy metrics without considering the importance of prioritizing faults with most adverse impacts. The impact assessment through novel weighted multi-criteria key performance indices (KPIs) is thus needed to put the right attention on different faults considering their effects in terms of energy consumption, greenhouse gas (GHG) emissions, energy costs, thermal comfort and indoor air quality (IAQ) according to their severity and occurrence frequency. For example, (Y. Chen, Lin, et al., 2022) developed a simulation-based framework for evaluating the fault effects in FCU. They also proposed a metric, namely the fault symptom occurrence probability (SOP), to assist the fault prioritization. (Lu et al., 2021) conducted a comprehensive fault impact analysis and robustness assessment of the high-performance control sequences from ASHRAE Guideline 36 using Modelica-based simulation with KPIs to evaluate fault impacts from the aspects of energy consumption and energy cost, control quality factor, thermal comfort, ventilation, and the power system.

6.4.3 Scalability and Transferability

HVAC systems in large commercial buildings are typically designed and constructed in a unique way for each building. Each building may have its own unique boundary conditions, such as weather, occupancy, and internal load schedules that vary daily. As a result, data-driven FDD method developed for one building may not be applicable to another building. The following research areas may be considered to improve the scalability and transferability of a data-driven FDD method.

Hybrid approach. Data-driven FDD methods require a considerable amount of data to exploit enough reliable and robust extracted knowledge. However, data-driven FDD methods generally cannot extrapolate well beyond the range of training data related to specific boundary conditions, limiting then the scalability and transferability of detection and diagnosis logics among different systems (Frank et al., 2016). The expert-based approach, in contrast, has a strong capability for replicating and transferring expert diagnostic reasoning, especially in cases where initial information is not enough for deploying a data-driven process. Integration of both approaches may significantly improve the robustness, accuracy, and generalizability of FDD tools designed for building energy system applications.

Transfer learning. Besides the hybrid approach, transfer learning is being investigated as a fully data-driven solution to address the scalability issues of FDD strategies. Transfer learning (Pan & Yang, 2009), can effectively reduce the time to re-collect labeled data and re-train FDD algorithms, and thus reducing developmental costs. Recently, there has been some discussions about transfer learning in the building FDD field. For example, (Dowling & Zhang, 2020) demonstrated a transferable Bayesian classifier for detecting supply fan degradation fault due to fouling filter in a VAV system. (Miyata et al., 2021) demonstrated transfer learning on convolution neural networks (CNN) for fault diagnosis of central chilled water plants. (X. Liu et al., 2021) developed a transfer-learning-based CNNs for fault diagnosis of chillers. More studies are needed to further explore the potential of using transfer learning to improve the scalability of data-driven FDD.

Metadata schemas. Metadata schema or semantic data model allows data from different buildings to be described in a consistent and standardized manner. Using a common metadata schema not only eases the data collection process (as mentioned in Section 6.2.1), but also makes a data-driven FDD method more generic. Without a common metadata schema, a data-driven FDD method must be hard-coded to a specific data source of a specific building, thus limiting its scalability and transferability. In addition, metadata schemas can provide well-organized information about the nature of the data (e.g., type of sensor, causal relationship between points), which allows expert knowledge to be incorporated into a data-driven method more effectively. Project Haystack, Brick, and the recent ASHRAE 223P standard (Pritoni et al., 2021) are good options of metadata schema for building energy systems.

6.4.4 Interpretability

For a market-oriented FDD product, its interpretability (i.e., the ability to explain how a fault is detected or diagnosed) is very important. In fact, building professionals tend to be suspicious of the output of data-driven processes because they are unable to fully understand the model inference mechanism (Fan et al., 2019). It is becoming more and more important to develop FDD tools that are capable of providing feedback about the reasons behind a certain detection or diagnosis result with robust indication of the supporting and conflicting evidence towards it.

In this respect, hybrid approaches, such as BNs that incorporate causal relationships between faults and symptoms, show great advantages. However, for pure black-box approaches, such as ANN, users are often unable to explain how they make decisions due to the models non-intuitive and non-transparent nature. The development of an explainable framework can help increase user confidence in such models. While interpretability continues to be a challenging task, a few studies have focused on this issue in recent years. For example, (Madhikermi et al., 2019) used Local Interpretable Model-agnostic Explanations (LIME) to explain behaviors of SVM and ANN in detecting AHU heat recycler fault. (G. Li et al., 2021) developed an explainable CNN-based FDD by utilizing Gradient-weighted Class Activation Mapping and validated it using the ASHRAE 1043-RP data.

6.4.5 Cyber Security and Data Privacy

Modern BAS are typically connected to internet or enterprise network to reduce operational cost and increase automation. There are many benefits that a BAS can gain through the network connectivity, such as remote management, cloud computing, and data sharing (Fu, O'Neill, Yang, et al., 2021). However, a network connectivity also makes BAS and the associated systems and devices potential targets of cyber attacks, leading to comprised systems and loss of credential information. For building energy systems, cyber attacks can disrupt the normal operation and result in serious consequences, such as occupant discomfort, energy waste, equipment downtime, and disruption of grid operation (Fu, O'Neill, Yang, et al., 2021). Therefore, there is a need for a FDD framework that takes cyber security and data privacy into account. For example, researchers are currently developing a Cyber Defense and Resilient System (CYDRES) that employs fault detection, fault diagnostics, fault prognosis, and cyber-resilient control scheme to enhance Grid-interactive Efficient Buildings (GEBs) tolerance to both cyber-related and physical faults (Fu, O'Neill, Wen, et al., 2021; Fu, O'Neill, Yang, et al., 2021).

6.4.6 User Experience

Each of the previously mentioned future challenges will to some extend affect the user acceptance of data-driven FDD services. The user/client is usually the one paying for the service, thus creating a successful user experience will also benefit user acceptance of FDD as a service and ease a widespread implementation in real buildings. A positive user experience depends on how information is presented to the user to be able to understand what is happening in the building/system and why. In this regard, dedicated dashboards for different building users (facility managers, building owners, building tenants) are of utmost importance (Peng et al., 2022). A proper visualization of measurement data predicted data from data-driven models and case-specific key performance indicators all contribute to a better user experience and thus higher acceptance of data-driven methods among clients/users. A proper indication of the severity of a fault is important for the person, usually the facility manager, who has to repair the faulty systems. Clustering and ranking faults/alarms based on their severity and criticality for the operation of the system/building is a time-saving measure for the facility manager in an often-hectic workday. More research is needed to understand how to improve the user experiences for data-driven FDD methods.

6.5 Conclusion

This chapter provides a comprehensive review of the process, systems studied, and evaluation metrics for data-driven FDD. Existing literature provides promising methods and frameworks for implementing data-driven fault detection and fault diagnosis, step by step from collecting data to detecting anomaly to isolating root causes. Data-driven fault prognosis remains to be further developed. In terms of system studied, many studies exist that apply data-driven FDD methods to typical building HVAC systems (e.g., AHU-VAV and chiller). However, most of the studies are based on simulated or lab experiment data. Many types of evaluation metrics have been reported in the literature which are sufficient for data-driven FDD performance evaluation. Overall speaking, existing literature has laid a solid foundation to demonstrate the feasibility and benefit of using data-driven FDD. Yet significant challenges still remain for a wide market adoption of data-driven FDD methods. These challenges include real time and real building implementation that is subject to data uncertainties; method performance benchmarking in real buildings; fault impact analysis; method scalability and transferability; fault interpretation; cyber security and data privacy; and user experience. It is our hope that this review would provide insights and directions for practitioners and researchers to develop the next generation data-driven FDD products.

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7. Building-2-Grid

- Understand the different Building-2-Grid services, strategies and applications.
- Identify what components and systems play a role in Building-2-Grid services.
- Gain an insight into the current deployment and readiness of Building-2-Grid services and technologies.
- Learn about the challenges in the development of Building-2-Grid services.
- Understand the difference between direct and indirect control of flexible assets

7.0 Introduction

The transition from fossil fuels to fluctuating renewable energy sources requires a drastic change in the operation of the current energy systems and energy grids. Simulation studies and demonstration projects have shown the potential of demand-side management (i.e., the capacity to adjust dynamic energy loads) to alleviate the challenges in the energy infrastructure, e.g., voltage and frequency stability in electrical grids, peak power limitation and local bottleneck effect in thermal and electrical grids, high costs and CO2-intensive operation of peak power generators, negative electricity prices, costly reinforcement or extension of the networks, faster deterioration of hydronic networks caused by the unstable operation.

Building energy flexibility is the ability of a building to adapt or modulate its short-term (a few hours or a couple of days) energy demand and energy generation profile according to climate conditions, user needs and energy network requirements without jeopardizing the technical capabilities of the building systems and the comfort of occupants . Building energy flexibility strategies (also known as demand response) thus allow load control/modulation to provide building-to-grid (B2G) services to the local energy grids. These B2G services support the matching of the energy demand profile with the energy supply profile in smart grids dominated by RES, but also help to tackle the aforementioned grid challenges and thus contribute to reaching the sustainability goals of the building sector (see Fig. 7.1).

This chapter aims to provide a rapid overview of the B2G services, including their potential and challenges, and give some insights on the latest pilot projects applying building energy flexibility strategies.

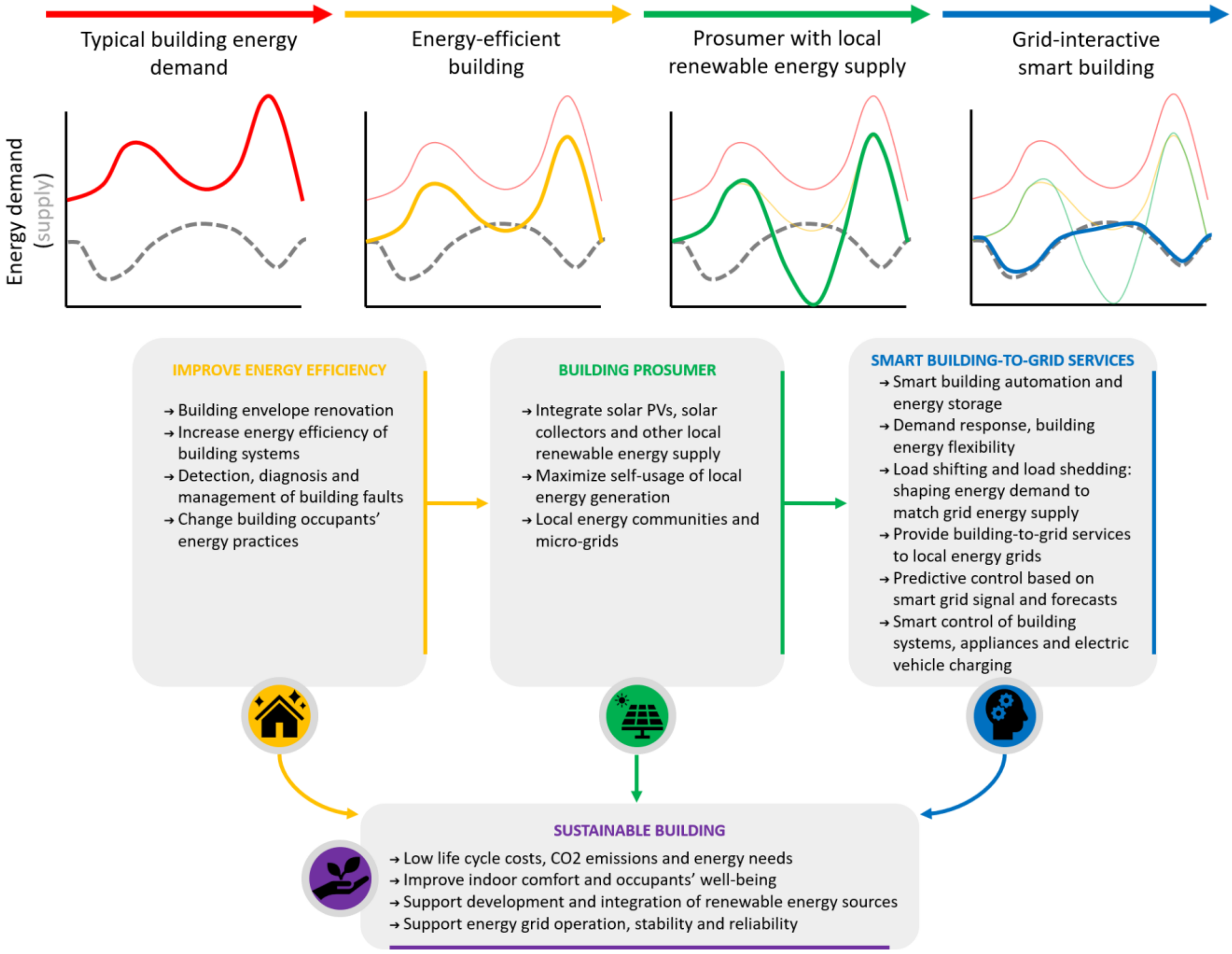

Figure 7-1. The establishment of B2G services in energy-efficient smart building prosumers (supplying energy locally with integrated RES) interacting with smart energy grids to support a more sustainable building stock and overall energy system. *Source*: Reproduced from Johra., 2023.

7.1 B2G Services and Strategies

There are two main categories for the demand response control strategy of energy end-users: *direct control* and *indirect control* (also known as incentive-based or explicit control). Direct control strategies regulate the distributed energy end-user systems via a direct two-way communication link: the devices are directly told when and what power to use according to technical limitations and comfort and service levels pre-set by the occupants or building owners. Indirect control strategies influence the distributed energy end-user systems via an incentive or penalty signal that the aggregators or the grid operators broadcasts and to which the local controllers of end-user systems react (Halvgaard et al., 2013, Madsen et al., 2015). This incentive or penalty signal could be, e.g., an energy spot price, an energy price forecast, or a CO_2 intensity of the energy production in the grid. Each building and end-user integrate this incentive signal together with a weather forecast, occupancy prediction and estimate of what energy demand modulation is possible and adjust their building system operation to minimize total energy costs or CO_2 emissions over a prediction and control horizon of a few hours or days (Paterakis et al., 2017, Halvgaard et al., 2012). This would result, for instance, in electric vehicles and domestic hot water storage tanks being turned off during the high energy price periods to decrease load demand and, on the contrary, be activated and store energy during the low energy price periods to increase load demand.

The following figure (Fig. 7.2) illustrates some common demand response strategies that can be activated depending on the grid's challenges and needs.

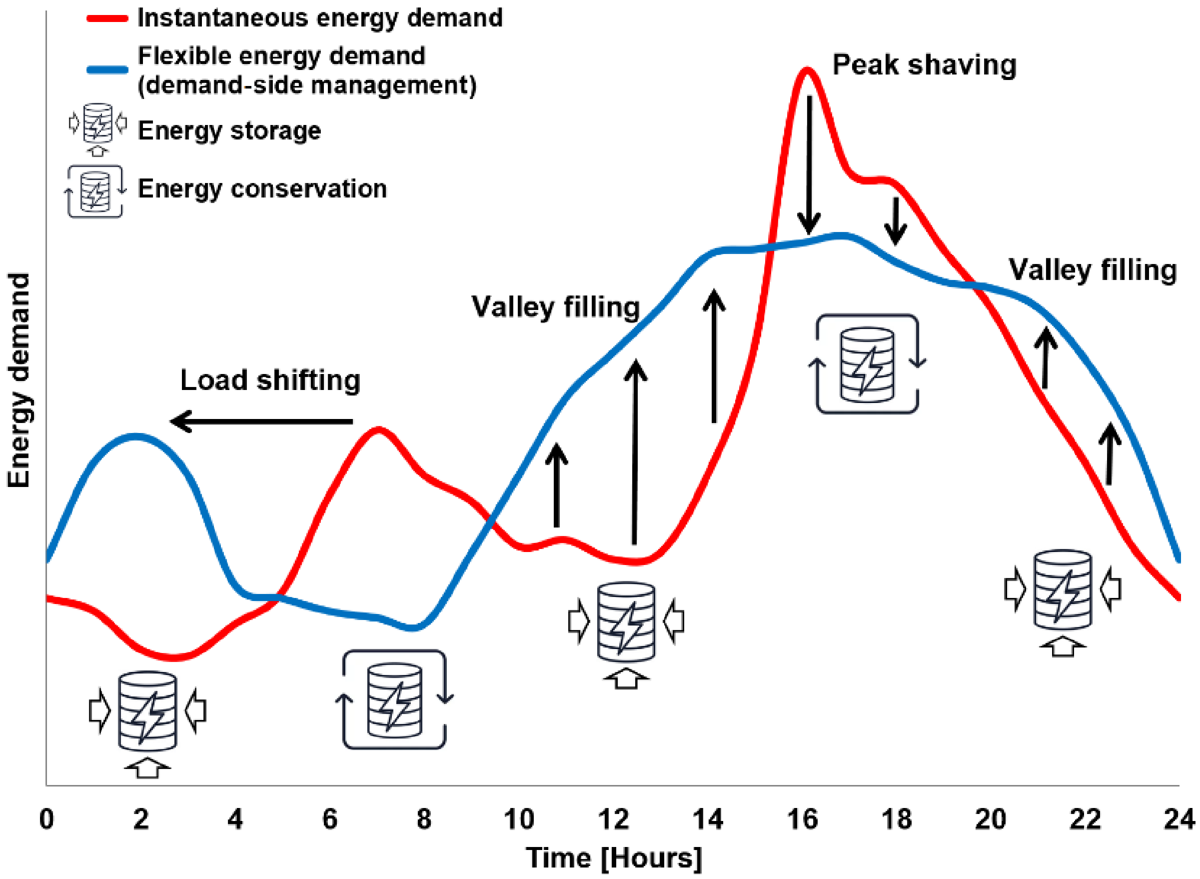

Figure 7-2. Illustration of different demand-side management / demand response / building energy flexibility actions. Peak shaving: Reduction of the energy peak demand. Load (time) shifting: Anticipate or delay the energy use. Valley filling: Increase energy use over a short period of time when the energy demand is lower than the energy production; this energy can be stored for a predicted period of energy shortage or peak shaving need. Valley filling can also be the result of a rebound effect following peak shaving. *Source*: Modified from Andersen et al., 2019.

As illustrated in Figure 7.3, the demand response potential of a building depends on the individual energy flexibility capacity of various components. Among these components, certain systems have the potential to perform load shifting (heating system, ventilation, electric vehicles, certain white goods and appliances), while other elements provide direct energy storage (electric vehicles, photovoltaic batteries, building envelope and thermal mass, hot water storage tank), or energy generation (heat pump, photovoltaic panels).

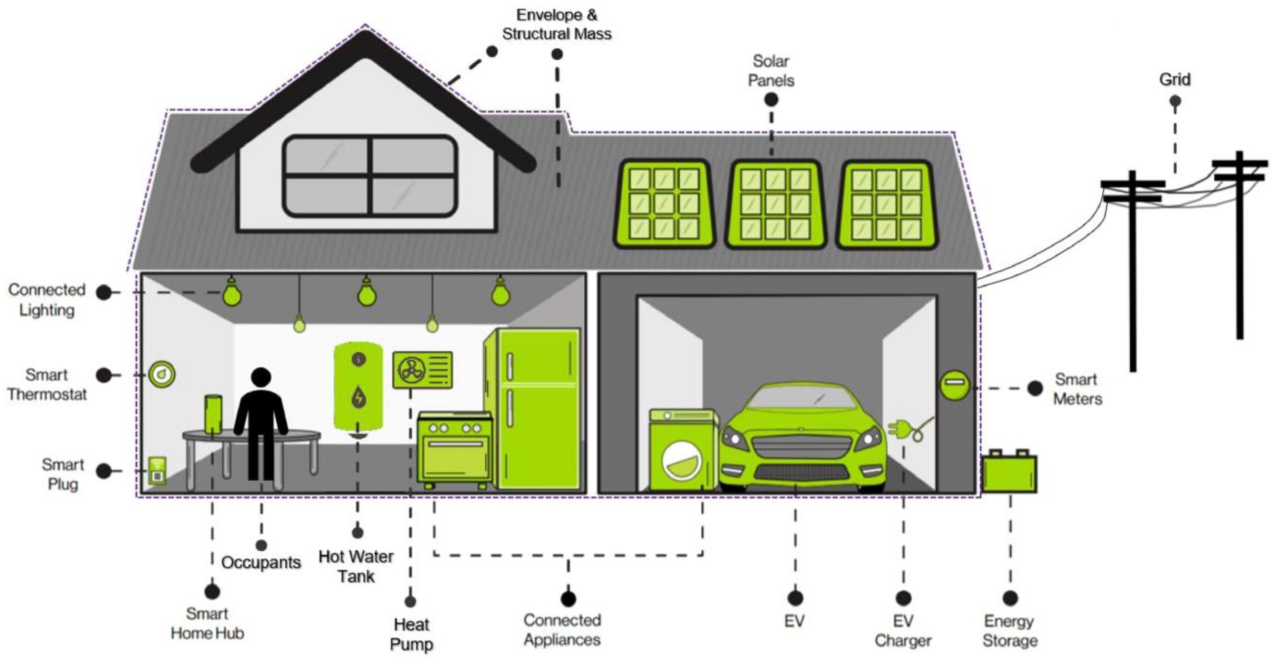

Figure 7-3. Components of a grid-interactive building that can perform demand response. *Source*: Reproduced from Li et al., 2021.

In order to effectively perform the aforementioned flexible load modulations by direct control, it is necessary to ensure proper two-way communication between the grid-interactive smart building prosumers (using, storing and/or supplying energy), the smart energy grids (local distribution grids and larger-scale transmission networks of electricity, gas, district heating/cooling), and the building occupants, owners and managers. The interaction between the building systems, appliances and the grid is facilitated by the adoption of appropriate smart home automation systems and dedicated smartphone apps.

In the case of demand response with indirect control, it is sufficient to only broadcast the incentive signal (typically, a price signal). For instance, in the Smart Energy Operating System setup (Madina et al., 2019), the price signal sent to the end-user is made of composite price signals, where each element of the final price is obtained by a controller solving specific grid challenges (see Section 5.4).

B2G services are fundamentally linked to the establishment of data-driven and data-sharing smart buildings. Indeed, to achieve any kind of direct or indirect demand response control, buildings need to provide some monitoring data to certain actors of the smart grids and energy markets. Moreover, they should be able to receive and interpret smart grids' signals to automatically perform adjustments to their energy profile via smart home technologies or building automation systems (BAS). Finally, to reward B2G services, the continuous efficiency and effectiveness assessment of the latter requires data-driven methods to generate building energy demand profile baselines (reference scenarios without demand response) and key performance indicators of energy flexibility computed with building operational data (Li et al., 2023).

7.2 Technology Readiness and Potential

With the current and future challenges of increasing energy demand and energy prices, energy supply scarcity and instability, service electrification, global warming, and the rapid expansion of intermittent renewable power generation, demand response and energy flexibility strategies are attracting more and more attention and gaining traction within the scientific community and the general public, businesses and policymakers.

The great potential of buildings to provide B2G services by means of demand response has been clearly identified by many research groups (Reynders et al., 2013; Le Dreau et al., 2016, Samad et al., 2016; Johra et al., 2018). For example, it has been estimated that efficient and flexible residential and commercial buildings providing B2G services could lead to a $100-$200 billion cost saving and a 6% reduction in US power sector emissions from by 2030 (Satchwell et al., 2021). Real-life large-scale pilot projects reported heating peak load reductions of 40-65% achieved by throttling heat pumps in a cluster of buildings (Müller and Jansen, 2019). If the current global demand response capacity at times of the highest flexibility needs for the building stocks is only 1% of the total electric power supply, it is estimated to reach 10% of the latter by 2030 (IEA Tacking report - Demand Response, September 2022).

In recent years, several large international projects, such as the ones under the umbrella of the IEA EBC projects Annex 67 (www.annex67.org), Annex 81 (https://annex81.iea-ebc.org), Annex 82 (https://annex82.iea-ebc.org), and Annex 84 (https://annex84.iea-ebc.org) strived to provide insight on the various aspects of B2G services and building energy flexibility, identify study cases, suitable assessment frameworks, tools and KPIs, determine stakeholders' interactions, business models, and analyse legislative challenges, technological barriers and acceptability from building occupants and owners (Jensen et al., 2017; Li et al., 2021; Li et al., 2023).

Currently, the different B2G service and demand response solutions have a technology readiness level (TRL) of 5 to 8. The different technologies for B2G services are mature, several pilot projects have been completed, and a certain number of commercial applications are now being deployed. With the current energy crisis and the forecasted risks of grid blackouts in several countries, there is no doubt that B2G services and demand response strategies will be massively deployed in the upcoming years. However, significant effort must be made to identify adequate business models and legislative frameworks for B2G services.

Flexibility services can be provided at multiple levels of aggregation: device level, zone level, building level, and building cluster level. The demand flexibility can be employed to meet specific local objectives, such as generating energy efficiency and capacity constraints or improving the self-supply from on-site or local RES. At the distribution grid level, these objectives can be broadened to manage congestion and resolve voltage issues in the electric grid with increasing intermittent renewable energy (Biegel et al., 2014; Kazmi et al., 2019; Wrinch et al., 2012). Global objectives can also be met, such as the reduction of the national peak power demand during critical days/hours to avoid blackouts and curtailments of a certain section of an electrical grid because of insufficient peak supply capacities. The reduction of peak power demand and the controllability of the demand greatly improves the CO2 intensity of the entire energy mix by promoting the viability of intermittent renewable energy sources and limiting the need to build, maintain, start and operate fossil fuel-based peak units.

For district heating and cooling systems, B2G services can improve the temperature difference between the supply and return lines of the network (and thus improve the energy efficiency of the system), reduce peak loads and network congestion (which typically lead to unfair heat distribution and service reliability) (Van Oevelen et al., 2021).

The flexibility from many households or buildings can be aggregated for participation in energy markets, e.g., on the day-ahead or imbalance electricity markets, or for provision of ancillary services, e.g., primary, secondary or tertiary frequency regulation by aggregating multiple resistive heating elements (Balint and Kazmi, 2019; Kazmi et al., 2019; Van Oevelen et al., 2021).

Aggregators control (directly or indirectly) a portfolio of distributed flexible energy consumers, producers and storage systems. The former can thus utilize this flexibility to participate in the electricity or heat markets for primary, secondary, and tertiary reserves (see Figure 7.4 and Figure 7.5).

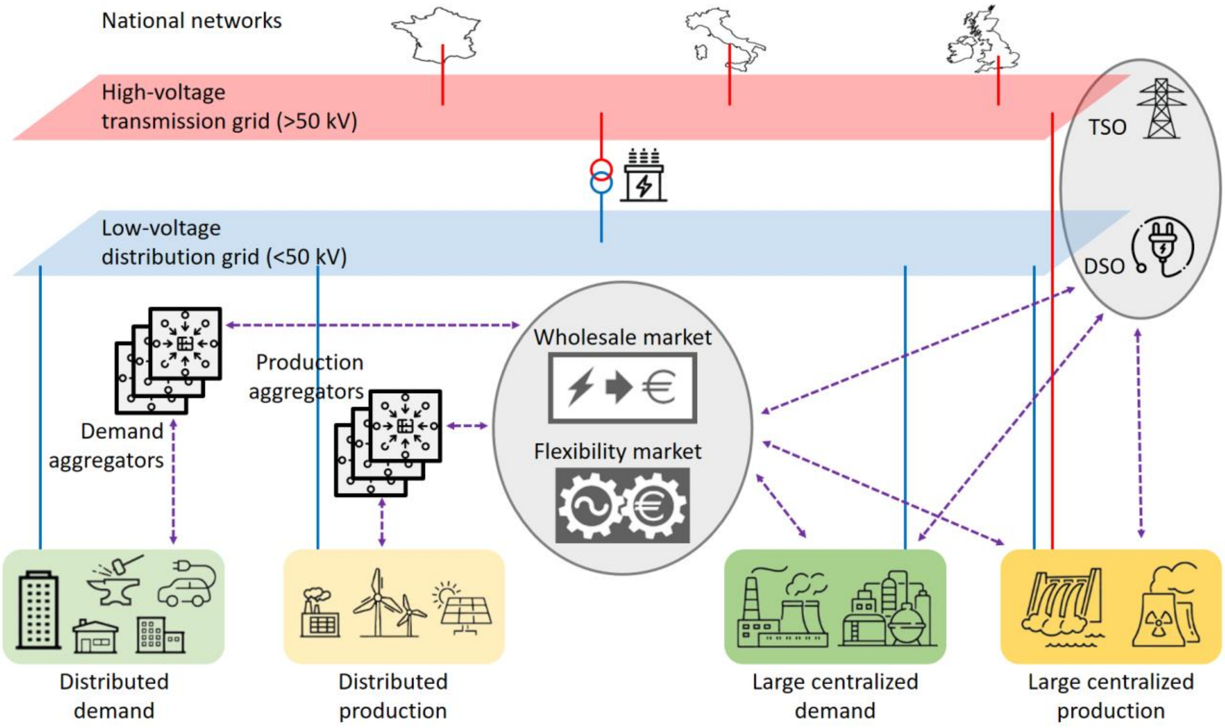

Figure 7-4. Integration of the B2G services/demand response/building energy flexibility in the smart electrical grid system with market mechanisms. The dashed purple arrows represent the communication interactions between the different actors of the electrical system: Distributed demand (residential buildings, office buildings, commercial buildings, charging stations for electric vehicles, small industries), large centralized demand (large industrial facilities), distributed production (wind farms, solar farms, combined heat and power plants, renewable energy sources integrated into buildings), large centralized production (nuclear plants, hydro-electric dams, gas-fired power plants). *Source*: Modified from Biegel et al., 2016.

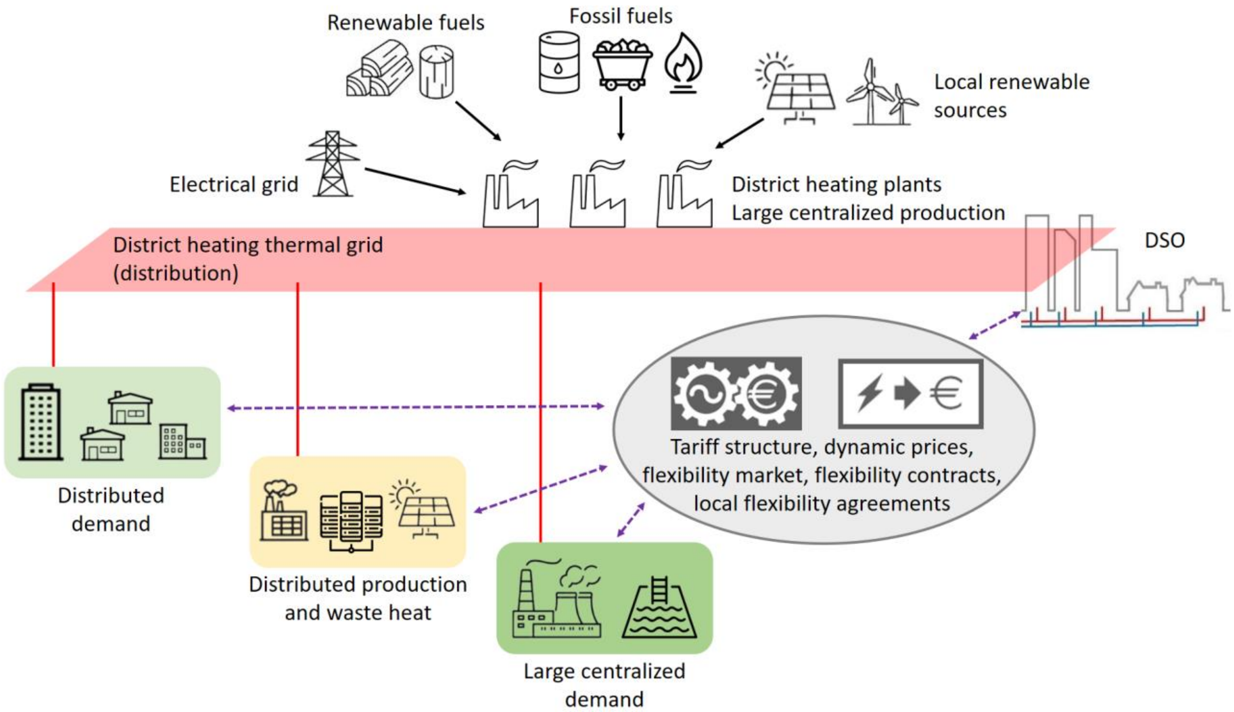

Figure 7-5. Integration of the B2G/demand response/building energy flexibility in the district heating network system with market and contract mechanisms. The dashed purple arrows represent the communication interactions between the different actors of the district heating system: Distributed demand (residential buildings, office buildings, commercial buildings, small industries), large centralized demand (large industrial facilities, large buildings), distributed production and waste heat (solar collectors, combined heat and power plants, booster heat pump stations, waste heat from industrial processes).

Direct-control demand response is usually organized around a *flexibility market*, such as the one hosted by the flexibility clearing house "FLECH" (Müller and Jansen, 2019). On such a flexibility market platform, the processes of opening a market offer, submitting bids, and clearing a market occurs before the delivery of the actual B2G service, i.e., the demand response event. The flexibility market is the intermediary between the sellers (single large energy end-users or aggregators of distributed energy end-users) and the buyers (DSOs and TSOs) of energy flexibility (see Figure 7.6).

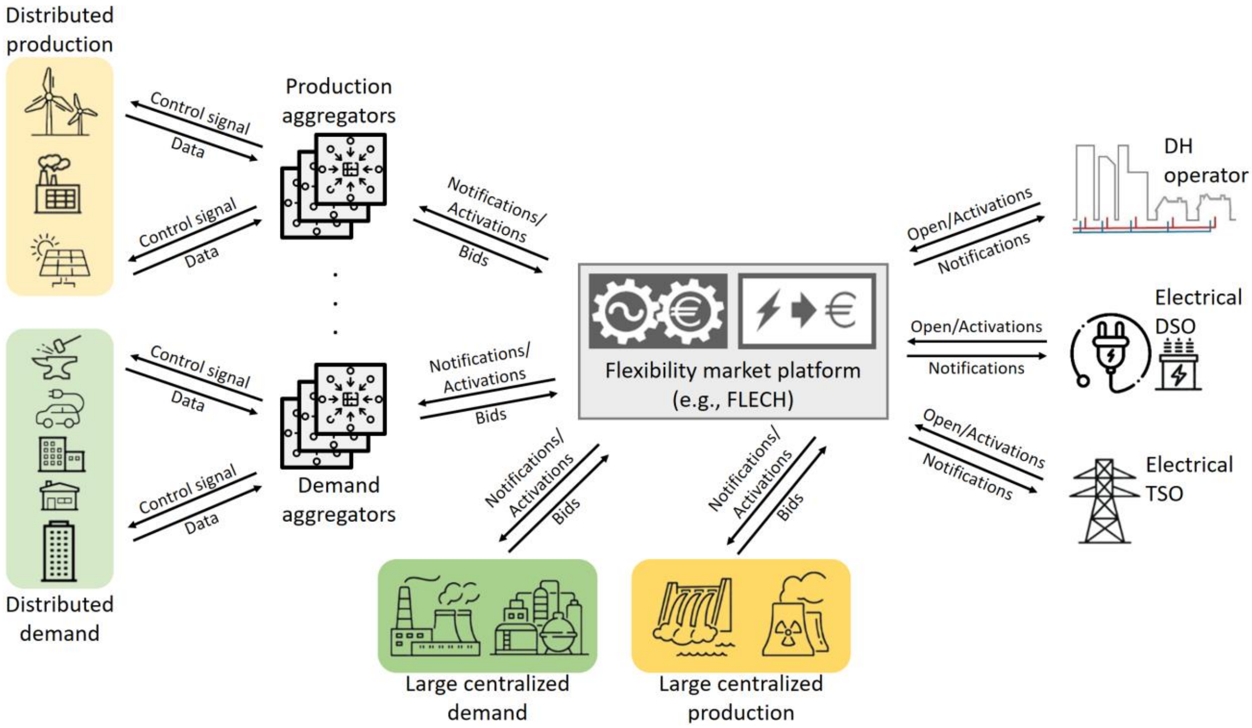

Figure 7-6. Market-based direct control for demand response and B2G services with flexibility buyers (DSOs and TSOs) and flexibility sellers (aggregators of distributed energy end-users and productions, large energy end-users and productions). The aggregators collect the data from the distributed energy end-users and distributed energy producers to estimate their portfolio's flexibility and bid on the markets that are opened by the potential buyers or offer their flexibility products (load shifting events) on the flexibility market. If a buyer accepts and activates a bid, the control signal for direct control is sent to the seller, and the corresponding market is closed/cleared. *Source*: Modified from Müller and Jansen, 2019.

Similarly to the wholesale energy markets, this flexibility trading at the wholesale level may be financially viable for aggregators and large industries. However, for residential and small commercial participants, P2P (peer-to-peer) blockchain-based approaches are emerging as a solution for decentralized energy flexibility trading via the realization of smart contracts by a crowd of small prosumers (Wu et al., 2022).

P2P energy trading marketplaces and P2P energy flexibility marketplaces are starting to be deployed. For example, the *Suncontract* platform is fully operational in Slovenia and deployed in several energy communities, such as the renewable energy self-sufficient community of Zavrate (Suncontract, 2022). While trials in Western Australia experienced challenges with value capture, the technical feasibility of P2P energy trading was successfully demonstrated in the White Gum Valley trial involving 24 apartments (Western Power, 2022). Extending energy trading to incorporate flexibility trading has shown benefits for grid decentralisation, managing loads and near real-time settlement of demand response, as demonstrated in an Italian pilot project in collaboration with a DSO (Glavan et al., 2019).

7.3 The Smart Energy Operating System: example of a data-driven B2G service framework

According to the scientific literature on the topic and the experience from pilot projects (e.g., Center Denmark: smart energy hub), most of the building-related demand response methodologies are based on indirect control schemas: typically price-based control. The Smart Energy Operating System is a framework for hierarchical modelling, forecasting and market operations (see Figure 7.7). At the top level, it consists of conventional markets, but at the lower levels, it employs methods combining direct and indirect control. In addition, the Smart Energy Operating System is designed as a hierarchical system for data handling and an information exchange framework. It thus ensures a unique coherence across all relevant spatial and temporal aggregation scales, with a focus on multi-objective criteria like energy efficiency and flexibility.

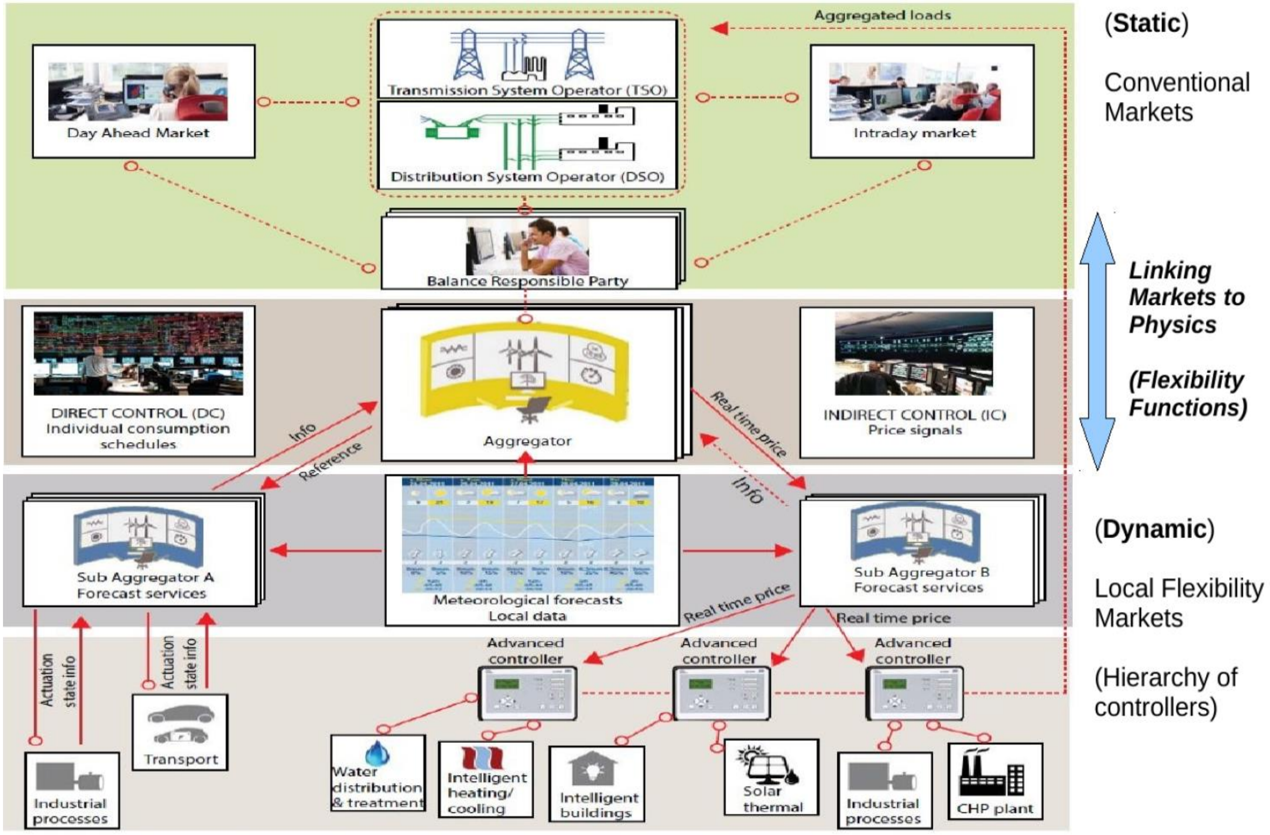

Figure 7-7. The Smart Energy OS.

The Smart Energy Operating System relies on the Minimal Interoperability Mechanisms (MIMs) roadmap, which aims at providing building blocks for an efficient digitalization of society. It provides functionalities across different but related domains like energy, transportation and water. Its intent is not to replace existing market mechanisms where end-users bid at the appropriate markets. On the contrary, it reinforces the latter with a MIMs-compliant framework for an efficient scale-up of local flexibility concepts (e.g., large-scale integration of wind and solar energy) while supporting local initiatives like district heating networks and energy communities.

The Smart Energy Operating System offers unique frameworks and data spaces for the exchange of information between all relevant aggregation levels that have been established. More specifically, it contains a framework of spatial and temporal hierarchies for ensuring that forecasts (e.g., wind power generation forecasts) are coherent across all relevant aggregation levels (Sørensen et al., 2023). The Smart Energy Operating System focuses on the integrity, privacy (including GDPR), transparency, security and reliability of the handled data. In this framework, the computations are done at many levels of the system hierarchy. The Smart Energy Operating System for Power Systems, Home Energy Management Systems (HEMS) and Home Management Information Systems (HMIS) can be used to provide information about the aggregated flexibility which can be offered from a particular building or an entire energy communities.

Energy efficiency and flexibility of residential buildings are important examples where design-specific data exchange metrics have been adopted. A key element of the Smart Energy Operating System data exchange framework between energy end-users and grid operators is the Flexibility Function (see Figure 5-5, Junker et al., 2018). The Flexibility Function is one of the fundamental MIMs-related features and represents a condensed data exchange framework which is used to create a coherent link between the low-level physics (e.g., the thermal inertia of the buildings) and high-level electricity markets. Moreover, the Flexibility Function contains all relevant information for the balance responsible parties and the distribution grid operators, while preserving privacy. The Flexibility Function is also used for sector coupling and for hybrid energy systems, e.g., buildings with both district heating connection and heat pumps. Finally, the Flexibility Function can be applied at all aggregation levels, e.g., for the appliance, the building, the district, the city, or larger regions. The integrated standard Flexibility Function for activating flexibility at all levels and across all relevant energy vectors implies that flexibility and interoperability can be obtained everywhere using low-cost technologies. The simplicity of broadcasting price signals for activating demand-response entails that all appliances can contribute to unlocking the needed flexibility at the relevant spatial and temporal coordinates. At the same time, the end-user can easily set up local preferences in a weighted combination of costs, emissions and energy efficiency goals/focus. The overall simplicity of the concepts ensures fast adaptation and stimulates an effective scaling-up of flexibility and demand response technologies on the market.

Another key element of the Smart Energy Operating System is its grey-box modelling approach (introduced in Section 4.3.1.). Grey-box models have low computation needs and allow for real-time data from sensors and measurements to improve the forecast and control performance.

The Smart Energy Operating System concept has been demonstrated on a large scale in the *ebalanceplus projects– Smart energy flexibility for distribution grids* and *SmartNet projects* (EU H2020).

7.4 Commercial Products, Services and Deployment

Over the last few years, an ever-increasing number of smart distributed energy resources and connected devices in buildings have been deployed and have the potential for significant aggregated demand response for load shifting and peak demand shedding. This building demand response capacity could reach 250 GW globally by 2030, in addition to the 50 GW of flexibility capacity from the smart charging of electric vehicles. However promising, the deployment growth is too slow to meet the sustainability goals of the green energy transition (IEA Tracking report - Demand Response, 2022). Nonetheless, the current energy crisis and threats of local blackouts and grid curtailments are opportunities to accelerate policy frameworks for demand-side flexibility and incentivise stakeholders to significantly speed up the systematic deployment of B2G technologies and services. This section aims at reporting the recent advances in pilot projects and commercially available B2G services providing demand response.

In France, the demand-side flexibility market is rapidly increasing, with selected bids totalling 2.4GW in 2022 (IEA Tacking report - Demand Response, 2022). As a response to the risk of electric power supply shortage during the winter of 2022, France has launched a public awareness program that indicates to the general public what regions of France are under imminent threat of electric grid blackout. Similar to storm or heatwave forecast alerts, this blackout risk mapping aims at encouraging the people of the zone of concern to lower their electricity usage during critical periods to avoid selective power cuts (www.monecowatt.fr). In addition, 4.3 million clients have subscribed to a low-tariff/high-tariff program for the automated control of their domestic hot water production with an electric boiler. This tariff structure can also be used to perform direct control (curtailment) of sanitary hot water boilers to shed electric peak demand in critical zones. Load shedding of up to 2.5 GW could thus be achieved. The French DSO Voltalis got contracted by the French government to provide a 721 MW of load-shedding capacity from residential and commercial buildings (below 1 MW) only[13].

In the United Kingdom, 528 MW of one-year-ahead auction demand-side capacity and 1 GW of four-year-ahead auction demand-side capacity have been secured in 2022 [IEA Tracking report - Demand Response, 2022). British private energy providers, such as *Octopus Energy Ltd* (https://octopus.energy/), are popularizing variable electricity spot prices for households combined with smartphone apps designed to perform indirect demand response to alert and incentivise them to use more electricity and charge their electric vehicles during low-price periods, and use less electricity during high-price periods. Large-scale coordinated load-shedding experiments by these energy providers have shown that the UK's peak energy demand could be lowered by 10% when residential buildings perform demand response. Direct control of smart home appliances and smart EV charging should be deployed in the near future.

In Belgium, in 2021, 8% of the 4.45 GW four-year-ahead flexible capacity auction is covered by demand-side management and storage (IEA Tracking report - Demand Response, 2022).

In Denmark, the electricity spot price on the *NorthPool* market varies a lot. The adoption of smart variable tariffs by the general population and the electricity price forecasting displayed in newspapers next to the weather forecast have induced noticeable changes in energy habits. A shift in the time of energy use from peak hours to night hours has been observed for laundry, dishwasher and EV charging.

In central Europe, *Lerta* (https://lerta.energy/en/for-business/) is a capacity aggregator combining the demand flexibility of hundreds of energy end-users into a virtual power plant spanning over Poland, Hungary, Czech Republic and Romania. The clients are incentivised via variable spot prices and nudges for peak power shedding, while the resulting demand flexibility is traded on the capacity market.

At a global scale, it is estimated that commercial and residential energy storage systems represent 3.7 GW in 2020 and could reach 510 GW in 2030. Moreover, smart home EV chargers should be massively deployed in the upcoming years, going from 117 000 in 2020 to 28.7 million in 2030 (IEA Tracking report - Demand Response, 2022).

A list of recent B2G pilot projects is given in Table 7.1.

[13] URL: group.voltalis.com/en/empty/a-721-mw-major-contcat-to-voltalisdemand-response-6251

Table 7-1. Summary of B2G real-life applications.

Ref	Name	Country	Customer type	Component delivering B2G service	B2G strategy	B2G control strategy	Link
1	StryDinVarmePumpe	DK	Domestic	HP	Network Peak Shaving and Load modulation	Direct and Indirect	attached PDF
2	Customer-Led Network Revolution project	UK	Mix *	HP, Home appliances, EVs, PV	Network Peak Shaving	Direct and Indirect	http://www.networkrevolution.co.uk/
3	GridWise Olympic Pen-insula Demonstration	USA	Mix	All domestic and non-domestic loads	Network Peak Shaving	Direct and Indirect	https://www.pnnl.gov/projects/transactive-systems-pro-gram/gridwise-olympic-peninsula-demonstration
4	TotalFlex	DK	Mix	HP, Home appliances, Evs	Grid and end-customers requirements	Direct and Indirect	https://totalflex.dk/In%20English/
5	iPower	DK	Mix	HP, White appliances at homes and stores	Mix	Direct and Indirect	https://ipower-net.weebly.com/
6	Greater Manchester Smart Energy project	UK	Domestic	HP	Network Peak Shaving	Direct and Indirect	https://gmgreencity.com/smart-energy-team/
7	EnergyLab Nordhavn	DK	Domestic	HVAC	Network Peak Shaving	Direct and Indirect	http://www.energylabnordhavn.com/
8	eFlex	DK	Domestic	HP and other home appliances	Network Peak Shaving	Direct and Indirect	https://www.slideshare.net/JonathanDybkj/the-eflex-pro-jectlow
9	LINEAR	BL	Domestic	Home appliances, EVs, PV, Batter-ies, TES	Mix	Direct and Indirect	http://www.s3c-project.eu/News/89/LINEAR.html
10	READY	DK	Domestic	HP	Network Peak Shaving	Direct	http://www.smartcity-ready.eu/wp-content/up-loads/2021/02/Final-Publishable-Summary-Report-READY_v2.pdf
11	Your Energy Moment Zwolle	NL	Domestic	Home appliances	Network Peak Shaving	Indirect	https://www.rvo.nl/sites/de-fault/files/2013/09/Jouw%20Energie%20Mo-ment%20UK.pdf
12	EcoGrid	DK	Domestic	HP	Network Peak Shaving	Direct and Indirect	http://www.eu-ecogrid.net/
13	EcoGrid 2.0	DK	Domestic	HP	Mix	Direct and Indirect	http://www.ecogrid.dk/en/home_uk/#hvad3
14	Fort Collins RDSI	USA	Mix	Mix	Mix	Direct and Indirect	https://www.fcgov.com/fortzed/
15	Peak Smart	AU	Domestic	Reverse cycle airconditioning (air to air heatpumps)	Network peak shaving/ emergency response	Direct	https://www.energex.com.au/home/control-your-en-ergy/cashback-rewards-program/air-conditioning-rewards
16	DRH	AU	Domestic	HP, PV, thermal storage	Peak shaving and load shifting	Direct and Indirect	http://desertrosehouse.com.au/
17	CalFlexHub	U.S.	Mix	Mix	Mix	Indirect	https://calflexhub.lbl.gov/
18	FED Flexible Energy Denmark	DK	Mix	Mix	Load modulation for cost and CO2 savings	Indirect	https://www.flexibleenergydenmark.dk/
19	CITIES/Novasol	DK	Domestic	Heat pumps	Indirect	Indirect	http://smart-cities-centre.org/dynamic-co2-based-control-of-summerhouse-swimming-pool-heating/
20	CITIES	DK	Domestic	Heat pumps	Mix	Indirect	http://smart-cities-centre.org/wp-content/uploads/Con-trol-of-heat-pumps.pdf
21	Uni-lab.dk/Industrial	DK	Industrial	Cooling house	Load modulation for cost savings	Indirect	https://www.uni-lab.dk/en/living-labs/konstant-living-lab-power-grid-in-eastern-jutland/

*domestic and non-domestic

7.5 Barriers and Challenges to Adoption

Although demand-side management and building demand response are gaining momentum in the energy system community and the general public, pilot and demonstration projects of direct control demand response are not yet followed by large-scale implementations and diffusion into the economic rationales and habits of the different stakeholders. The main current barriers and sociotechnical challenges to the adoption of these B2G services are summarized hereafter:

- **Regulatory challenges**: In most countries, the current legislative framework completely hinders the large-scale deployment of building demand response. The rules of the energy markets and grid regulation are either too rigid, inadequate or simply inexistent regarding B2G services and the proper financial incentives for the participation of distributed demand response resources in the energy market. In some energy markets, the aggregation of consumers by a third-party company is illegal or practically infeasible. Moreover, neighbouring regions interconnected to the same energy grid often have different regulations, which make it difficult for third-party aggregators to provide large-scale energy services (Paterakis et al., 2017). These regulatory challenges prohibit proper business development and optimisation of building systems towards the maximisation of B2G service capacity.

- **Technical challenges**: The development of B2G services faces certain structural barriers, i.e., the need to deploy a significant amount of metering, control and two-way communication equipment at the different energy end-users, prosumers and energy transmission systems in order to create a large-scale smart energy grid. Telemetry equipment has costs that tend to increase with the required sampling rate, response time and reliability. However, building demand response needs a rather high response speed and sampling rate to provide certain grid services, especially for electric grids. Another challenge regarding the deployment of such metering equipment is the clear lack of standardization and DSM-oriented regulation for two-way communication protocols in building management systems (BMS) and building automation systems (BAS). Furthermore, many buildings are already equipped with inadequate legacy BAS, which will not be replaced shortly. This largely hinders the compatibility and interoperability of the different DR and B2G technologies, often leading to inaccurate and incomplete data collection, poor responsiveness, and unreliable information flow between the energy end-users, the aggregators and the DSOs, flexibility market or centralized controller. Many pilot projects reported failures in the chain of communication which can result in a significant value loss in the case of large-scale commercial deployment. There is thus a need to develop scalable and adaptive data treatment methods to pre-process and combine the heterogeneous data swamp from multiple buildings into useful information for the B2G service aggregators or the energy flexibility markets (Paterakis et al., 2017; Olgyay et al., 2020).

  Finally, there is currently no consensus on how to assess B2G services and energy flexibility effectiveness. Many different Key Performance Indicators (KPIs) have been developed by the scientific community. Most of them are based on the comparison between a reference or baseline energy demand profile and the energy demand profile of the building when performing demand response. The quality of the energy flexibility assessment is thus directly dependent on the quality of the energy demand baseline estimate. However, there is no standard way to determine the customer baseline. A flawed methodology could allow participants to an energy flexibility market to change their baselines in order to get paid without providing real load reductions, which would undermine the economic reliability of the entire market. Moreover, the current KPIs look at many different aspects of B2G services and energy flexibility. Consequently, there is currently no suitable and transparent tools in order to evaluate, measure and verify the B2G service and demand response effectiveness of buildings (Paterakis et al., 2017; Li et al., 2021; Li et al., 2023).

- **Business and market challenges**: B2G services suffer from significant economic barriers, in particular the lack of clarity around economic benefits and programs for demand response (with direct or indirect control from the grids) on multiple small sources of flexibility and energy communities. If business models for B2G services are relatively well-defined for utilities and grid operators (DSOs, TSOs), the incentive is much less compelling for ESCOs, aggregators and households. Part of the savings generated by the DSOs and TSOs must be redistributed to the different energy end-users and the small actors to incentivise them to provide data and perform energy flexibility actions that optimize grid operation and efficiency. Nonetheless, there are different views regarding how DR providers should be compensated for their B2G services. Some advocate that the DR providers should be compensated below the energy market price because the former already benefit from cost savings due to the load shifting towards low energy price periods. Others argue that DR providers should be compensated at the full energy price of the market, similarly to the generators. However, not purchasing and not using energy is not the same as supplying it. Lastly, some would invoke that DR creates positive sustainable externalities and should thus be rewarded higher than the market prices (Paterakis et al., 2017; Olgyay et al., 2020).

  The absence of standard methodologies to study the cost-effectiveness and GHG emission reduction of demand response actions hinders the decisions to perform investments. The provision of B2G services, therefore, becomes an additional objective in an already very complex multi-objective building design accounting for investment costs, life-cycle costs, energy costs, environmental impacts, societal impacts and resilience of services. Building owners cannot quantify the indirect value streams of demand-side management. Building energy flexibility is thus not usually included in the financing scheme of districts due to the lack of certainty in revenues and program availability. More generally, there is a lack of large assessments of B2G potential at the city-scale or national level.

  Customer segmentation is another issue in the deployment of B2G services. Different programs and tariff structures have to be tailored for the different types of customers with various energy practices, comfort requirements, responsiveness and flexibility potential. In the case of buildings with multiple owners, the distribution of costs and benefits for shared systems performing B2G services, together with the liability of equipment failure, cannot always be clearly defined. The retributions of third parties providing forecasting, assessment, optimization, and verification to aggregators and energy end-users have yet to be defined (Paterakis et al., 2017; Olgyay et al., 2020).

  In the case of tariff-driven control of demand response, accurate dynamic tariffs reflecting the actual time-varying costs for the DSOs and TSOs are important. However, while the spot energy prices can be very dynamic on the wholesale market, the final price to the customers often comprises a large share of fixed costs, constant taxes and flat fees, therefore reducing economic incentive opportunities for demand response. The Smart Energy Operating System contains controllers which can establish dynamic tariffs constructed such that the tariff-related costs are large enough to solve the issues of the grid and account for energy losses (Dognini et al., 2022).

  In addition, several criteria of a B2G service market need to be determined and standardized: Minimum resource bid size, entrance fees, aggregation mechanism for multiple small energy end-users, geographic boundaries of aggregation, number, frequency and timing of DR event calls, load recovery period, response time, fixed trading charges. Moreover, the roles and responsibilities of DR aggregators remain unclear.

Finally, the interest and views of the different actors and stakeholders in DSM are not necessarily well aligned, which impairs the proper business development of the latter. Most of the DR resources are connected to distribution networks. A good collaboration between the TSOs and DSOs is thus crucial. The latter use DR to tackle operational constraints on their grids, while energy retailers might use DR to mitigate high spot market prices. The flexible behaviour of certain energy end-users may induce lower energy rates which would then benefit all customers, even the ones not providing DR. Besides, DR might severely damage the business model of intermediate energy generators that are currently responsible for the regulation, load following and ramping. This could lead to the decommissioning of such power plants which, however, provide certain ancillary services, such as voltage support and system restoration, that cannot necessarily be provided by DR of the energy end-users in electric grids (Paterakis et al., 2017; Olgyay et al., 2020).

- **Human challenges**: The development of a structured energy flexibility market requires the different actors to become more familiar with such concepts. For instance, district heating utility companies have very little knowledge about the future problems that demand response can solve (Joh ansen and Johra, 2022). Significant efforts for the information and education of the different stakeholders is thus necessary. The DR and B2G service concepts must be introduced in a simple way and build on existing habits. Tailored education programs should target local communities and municipalities and explain the importance of DR to help with the resilience and sustainability of the local energy grids and how each participant can benefit from it and be rewarded for participating in it. One of the key challenges is that many buildings have multiple owners and stakeholders. It is thus very difficult to align their cost/benefit plan for all of them. In addition, many customers are reluctant to change their habits and energy usage practices because minimizing their energy bills or contributing to a sustainable system might not be their primary concern. Unlike the energy suppliers, energy end-users do not necessarily follow an economically rational behaviour, which limits the predictability of their effective involvement in B2G service programs. To reach a high responsiveness, engagement and acceptability of energy end-users in buildings, an appropriate communication approach must be taken to transmit DR information, e.g., smart home automation dashboard or smartphone apps. Specific nudging, incentive and feedback systems can be combined with transparent information to the energy end-users so that they can understand, choose and follow a tailored B2G service program/contract without being overwhelmed and confused by technical jargon and unclear offers from multiple parties (Paterakis et al., 2017; Olgyay et al., 2020).

- **Cybersecurity**: The multiplication of smart home automation equipment and wireless Internet of the Things devices, together with the ever-increasing complexification of network technologies in building automation systems creates concerning risks and vulnerabilities to malicious cyber attackers. Thus, securing the energy management systems of communities and smart grids from cyberattacks poses significant challenges. Building owners and occupants are also often concerned about the risks of personal information leaks or the loss of control on the building automation system, which could induce financial losses and safety and security issues (Paterakis et al., 2017). Together with a reinforcement of the cybersecurity technology and the legal framework, some technical innovations allowing decentralised control without sharing private user data are active research topics (Li et al., 2021).

- **Research and development challenges**: The R&D in the field of B2G services now needs large-scale pilot studies. However, these require a long preparatory phase which does not necessarily fit into the short-lived research projects that are usually funded. The support of DSOs to launch and extend these pilot projects is insufficient. This is probably due to the core of their energy trading business being, at the moment, too far from the different B2G services. Future B2G service pilot projects should include a large portfolio of energy end-users and a strong partnership between DSOs, TSOs, ESCOs, aggregators, curtailment service providers and other third-party actors

[Paterakis et al., 2017, Olgyay et al., 2020]. Finally, the reproducibility and transferability of B2G service studies must be improved. In particular, there is a severe lack of open datasets from buildings performing demand response. Most available datasets are of insufficient quality to be used by other researchers (Li et al., 2023).

7.6 Conclusion and Outlook

B2G services and technologies have a large potential to significantly improve the energy grids' sustainability and help tackle current energy and environmental challenges, solve local congestion and stability problems and mitigate the risks of blackouts on different electric grids. If the research and development in the field of building energy flexibility and demand response has been thriving over the last few years, the large-scale deployment of B2G services faces complex socio-technical challenges. Although load-shifting incentivizing programs based on variable energy spot prices are slowly diffusing in energy-related businesses and in the general population, significant efforts are required to set structured markets for demand response and B2G services. The business models and market perspectives around B2G services are still unclear for many stakeholders because of, among other things, a lack of appropriate legislative framework and standardized methods to assess the potential, effectiveness and benefits of demand response. In addition to addressing the aforementioned challenges, future B2G service R&D activities must include large-scale pilot projects to demonstrate the feasibility, cost-efficiency and acceptability of DR innovative business models and smart building technologies. These projects must include close cooperation between TSOs, DSOs, energy end-users, building occupants, building owners, building managers, architects, planners, ESCOs and third-party companies. The coupling and synergy of different local energy grids, neighbouring energy prosumers and transportation facilities should be at the core of the design and planning process of future energy communities and smart buildings.

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8 Case Studies Collection

- Overview of the methodology for collecting Case Study exemplars within Annex 81
- Provide stakeholders's perspective on lessons learnt from data-driven technology implementation

8.1 Introduction

The recent revolution in digital technologies and cyber-physical systems enables advanced control and operation of building services, unlocking the potential to reduce costs and improve energy efficiency. Edge computing and the Internet of Things (IoT) have allowed access to more diverse data and unparalleled computing capabilities at a low cost. Artificial intelligence and data analytics tools facilitated a new breed of data-centric approaches to deliver comprehensive energy performance assessment and predictive asset management — these are discussed to some extent in the previous chapters. Collectively these data-driven services enable new business models and support the development of a sharing economy, using platforms to connect users and data-driven services providers.

Progress in the digitalisation of building services has been slow, and the application of digitalisation for improving energy efficiency in buildings and unlocking value has yet to reach its full potential. Recent advancements in energy efficiency software and technological solutions have been successfully trialled, opening up exciting avenues for the sector. However, such solutions have been chiefly integrated into experimental projects and are not mainstream in the current state of practice.

It is familiar with technological innovations that hype usually raises expectations to unrealistic levels. While such hype might drive early adopters and researchers, actual adoption at scale is only possible when a clear value proposition is demonstrated in practice. The transition from technology development to implementation in the real world needs to account for stakeholder needs and understand what problem(s) a technology addresses. A stakeholder discussion session was organised as part of the activities undertaken within Annex 81 to discuss the opportunities and barriers to adopting such technologies. The discussion suggested that technology availability is not the main barrier but how this technology is integrated with the current state of practice and addresses actual end-user needs. The panel observed the limited availability of a) data and case study exemplars, ontologies and standards to support systematic pathways on real-world smart technology implementation, b) business cases and good economic incentives to enable clear implementation pathways, and c) the necessary skills to address system integration and interoperability challenges and develop solutions that align with existing processes and address stakeholder needs (Figure 8-1).

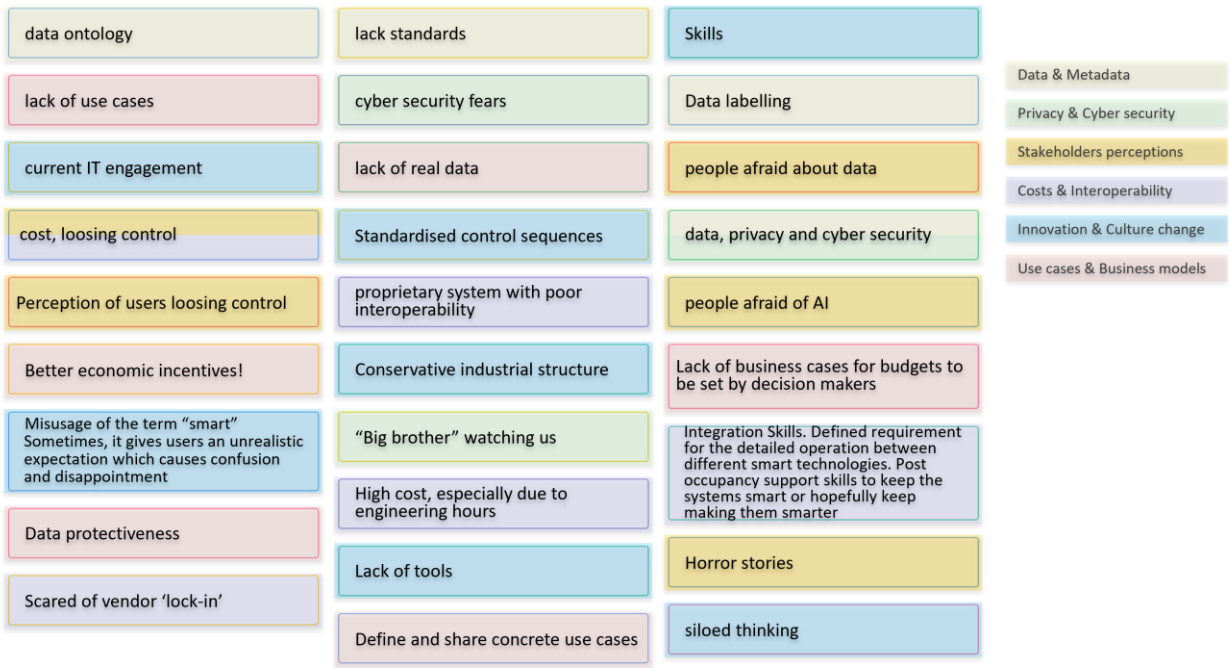

Figure 8-1. Stakeholders' perspectives on barriers to Smart-Buildings implementation. *Source*: IEA EBC Annex 81 Mentimeter Survey

Capturing relevant context, highlighting what has worked in practice and acknowledging the challenges encountered and lessons learnt are crucial to understanding the potential for technology innovation adoption, devising implementation pathways, and possibly catalysing innovation in the space (Figure 8-2). Real world exemplars of data-driven implementations are being compiled as part of the Annex 81 activities. The role of case studies is significant to reconcile the gap between a new technology (or approach) and its implementation in practice. Collection of case studies is an approach to mapping the landscape and it has been used in other similar contexts (for example, in the Historic Building Energy Retrofit Atlas developed in the IEA SHC Task 59/EBC Annex 76 project [HiBERTool, 2022]).

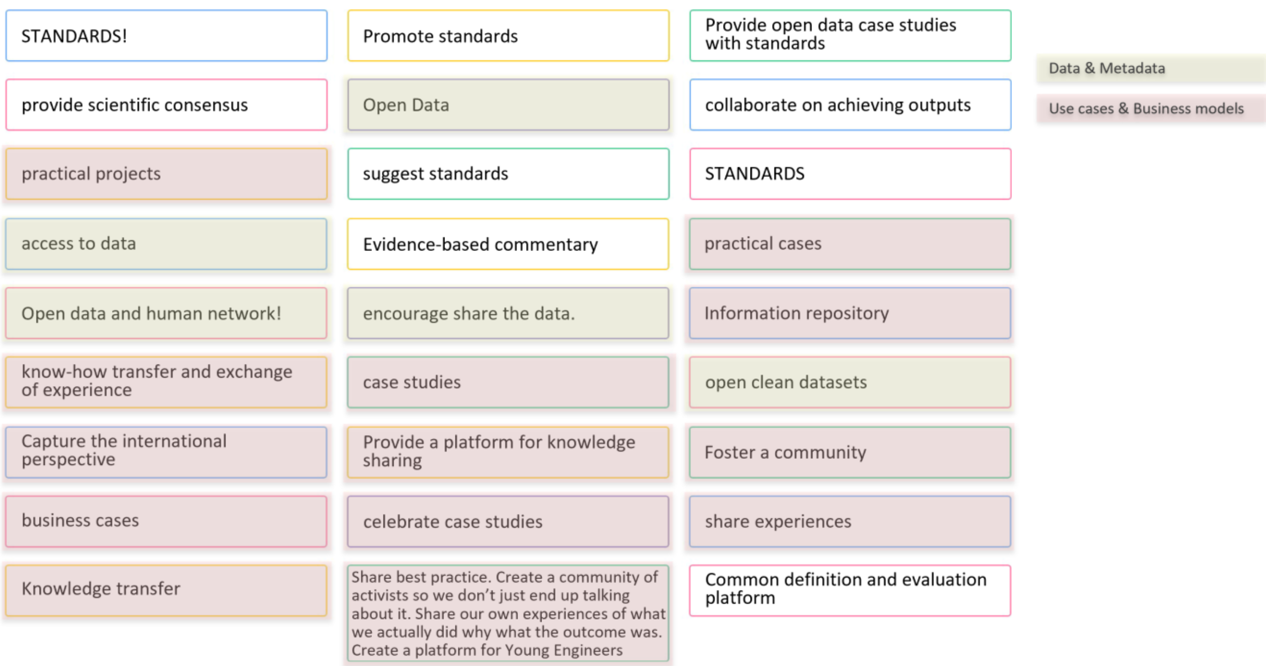

Figure 8-2. Stakeholders' perspectives on how Annex 81 can accelerate innovation in the space. *Source*: IEA EBC Annex 81 Mentimeter Survey.

The case study exercise undertaken aims to provide evidence to support knowledge and technology transfer, contextualised to enhance the accelerated adoption of such technologies in current practice. The case studies collected map the current technology and innovation landscape in non-domestic smart buildings and data-driven building services. The body of information generated aims at gathering evidence and narratives on the technical details, business cases, implementation journeys (e.g., benefits and disbenefits, challenges, lessons learnt and unintended consequences) and stakeholder stories associated with real-world implementations. The information collected is showcased open access on a dedicated website [Ruyssevelt et al., 2022] to generate reference knowledge primarily aimed at non-technical audiences, besides providing valuable inputs to support the definition of the tools developed within other Annex activities.

8.2 Methodology for case studies and business models collection

To understand any innovation's potential for adoption and success, it is necessary to capture the relevant context. In this regard, the case studies and business models exercise undertaken sought to a) collate knowledge gained from early adopters to understand the value proposition for the different stakeholders and how this can drive technological and business model innovation; b) distil the knowledge generated so that the benefits can be understood by a wider audience and support evidence-based decision making or the development of relevant policies. Either a particular building, technology or dataset could constitute a case study. The latter is particularly important as there is a clear need for datasets openly available - within a separate activity in the Annex, a catalogue of openly available datasets is being curated. Individually the case study descriptions aspire to highlight a particular facet of applying data-driven smart building technologies; collectively, the case studies help garner an understanding of the current state of practice and possibly identify a path forward.

The methodological approach to understanding the current state of practice, needs and challenges for real-world implementation of data-driven smart technologies involved several activities. These included a) a panel discussion comprising researchers, building managers and engineers, and smart-building services suppliers; b) interaction with different stakeholders; and c) a constant exchange of information with activities in other Annex 81 Subtasks. The stakeholders consulted agreed that: the case study exemplars should focus on collecting evidence on data-driven smart technology implementations in real buildings; capture stakeholders' perspectives and context; and summarise emergent business models, applications and specific technologies/technology stacks in an informative and accessible manner.

Following the initial scoping phase, a two-page template for case study collection was designed through an iterative process. A draft case-study template was generated from this knowledge, which was subsequently refined through co-creation workshops aiming to test the template with different stakeholder groups and ensure it captured relevant information to their field of work. The final template gathers general information on the case study, including location, technology installed, data availability and implementation status (Figure 8-3, top); information on technical details and business models, including project aim, implementation, value and business proposition, and impact (Figure 8-3, bottom left); and stakeholder stories and knowledge generation, including lessons learnt and actors involved in the process (Figure 8-3, bottom right).

The international network of experts participating in Annex 81 and/or their extended network were invited to participate in this research voluntarily. Interested participants who have been involved in the decision-making or implementation of smart building technologies were invited to fill in the case study template to reflect on their experiences. The coordinating team subsequently checked the contribution to ensure completeness of information, consistency in the level of detail provided across case studies, and language accessibility for non-technical audiences. An iterative email exchange with the contributor(s) was undertaken in case editing was deemed necessary before the final publication of the case study online.

A dedicated webpage (Ruyssevelt et al., 2022) was developed to host the case study exemplars collected and disseminate this information to relevant stakeholders such as academic, industry and government groups. Links to any supplementary information, such as visual information (e.g., images, workflows, graphs), building plans, models, datasets, publications, and wider project descriptions, are also provided where available. All material published in the web repository is shared under a CC BY-NC-ND 4.0 license agreement.

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 8-3. Case study template.

8.3 Synthesis of lessons learnt

The case studies collected mainly focus on MPC, digital twins, and FDD. The lessons learnt from the nine case studies collected at the time of writing this report can be grouped into four main themes: data quality and data collection; technology specification and implementation; occupants and thermal comfort; legal implications.

8.3.1 Data quality and data collection

Data quality and data collection was the most recurrent theme when discussing lessons learnt. Existing buildings are often monitored through several proprietary platforms, introducing data integration and maintenance challenges, for example, to ensure data continuity and quality across different data streams. This may represent a significant issue for the smooth operation of real-time tools, where data quality and cleaning are essential.

The richness of information is also paramount for simulation applications. One of the challenges in the current state of data collection and storage practice is represented by a lack of focus on cataloguing 'metadata', with the associated risk of limiting data usability. This process is often performed manually by interrogating additional knowledge sources (e.g., images from the building monitoring system, drawings, and site documentation) to interpret contextual information of the different data streams and bring meaning to the dataset. Conversely, individual equipment metadata (e.g., location, equipment hierarchy, nameplate information, model number, serial number) should be digitalised by including location and relevant tags as part of storing operational/telemetry data. Difficulties (and associated costs) in linking and reusing the data due to lack of meta-description was observed to potentially reduce the return on investment made to install logic control strategies.

Besides accurate metadata, the availability of a diversified and accurate set of data streams is critical to reducing uncertainty in energy simulation. For example, detailed information about occupancy and their interaction with the energy system was deemed crucial. To improve simulation results, submetering (e.g., lighting as a separate operation) was also necessary. However, some sensor typologies currently present some limitations for such applications. For example, some contributors advise against using infrared technology for people counting, especially for large-scale buildings, due to inaccurate measurements and high battery power usage. Some concerns were also highlighted with LORA sensors with issues related to the robustness of such technology and the current lack of large-scale manufacturing. Similarly, measurement of cooling (currently not standard practice) required dedicated, hard-to-install and costly sensors that may be difficult to justify. Care in representing complex building geometries, the mix-use of space, and the assignment of schedules to different thermal zones was also essential to reduce their contribution to simulation uncertainties.

Digitalisation of data is a prerequisite for the rapid development of building information modelling industry, as it allows reducing data loss at all interfaces (e.g., planning, construction, operation) as well as between different disciplines (e.g., HVAC planning, control engineering or building automation, facility management). Data-driven approaches and ease of reconfiguration are also necessary to ensure a more resilient building operation. A case in point is the recent Covid-19 pandemic, where significant changes in building utilisation and fast reconfiguration of ventilation systems were critical to increase the supply of fresh air to resume operation of shared spaces, such as offices. Available HVAC data from before and during the pandemic showed that the higher ventilation rates required (and possibly the associated increase in heating energy use in cool climates) increased energy demand throughout the 24-hour period.

8.3.2 Project specification and implementation

The limited amount (or, in some cases, lack) of information during the early phases of planning and the subsequent reliance on a high number of assumptions were identified as potential barriers to the final quality and reliability of data-driven smart technology implementations. Some components may require to be fixed at short notice during the execution phase, and adjustments to the complex simulation models (e.g., to reflect the changes implemented, undertake debugging and plausibility checks, and produce adequate visualisations of the results) may be lengthy and impractical. Indeed, decisions are often time-critical and extra time entails extra costs, which is always a problem in building construction processes. Additionally, assumptions might change during the planning and construction phase, with implications for using design values as simulation targets. Therefore, design models should be recalibrated with as-built values derived from monitoring data.

Several recommendations were made for the commissioning and trial operation phases. These include: the definition of suitable overall control strategies and operational modes for the whole system; provision of clear documentation for the commissioning phase of all major components (e.g., building automation, energy efficiency/performance targets, set points); functional quality management on component level. The installation of a quality management scheme during the trial operation phase was recommended to guarantee an efficient performance of the system; this allows working in synergy with the control engineers to define clear major operational modes and procedural steps to be tested. Similarly, operational digital twin models were observed to be able to automatically detect several typical problems with the installation of building services encountered during the commissioning phase (e.g., hydraulic errors; errors in the control logic).

8.3.3 Occupants and thermal comfort

Many lessons learnt concerned occupants' interaction with controls and their (perceived) thermal comfort. Occupants were more reluctant to accept and adjust to fully automated systems that did not provide them with the option for direct control or setting overriding. Similarly, setpoint variations were more likely to be accepted when the user did not notice the change. Training and knowledge transfer on the best-practice operation of a new data-driven smart technology and associated benefits was recommended as occupants may not operate the system as intended (e.g., some occupants favoured opening windows to utilising the HVAC system). Such issues are not new, and overwhelming empirical evidence identified similar findings both for non-domestic and domestic contexts (Parkinson et al., 2023, Behar, 2016, Salvia et al., 2020).

On some occasions, MPC algorithms were reported to improve the occupants' thermal comfort only marginally during automated operation. While this may be the case under certain circumstances, MPC algorithms offer the major advantage of providing an easy and transparent approach to balance the two conflicting objectives of ensuring parsimonious energy use while respecting high level of occupant comfort. Although such trade-off may vary between different users and boundary conditions (e.g., building fabric, prevailing climate, faultless system), it can be easily adjusted in the MPC implementation as a constraint in its mathematical programming problem. Thus, the adoption of MPC allows moving from an *ad hoc* approach in the building control strategy to a more dynamic and adjustable task-based approach with operational strategies that meet the specific needs.

8.3.4 Legal implications

Given the field's novelty, the legal implications of new implementations of data-driven smart technologies have still not been fully addressed or refined. For example, clear regulation is required in dealing with simulation results in the construction project context, as some information or changes to the functional technical description may occur. Another legal issue is related to the operators' contract, which often contains ‘energy saving targets’. These values are primarily measured in relative savings compared to a previous period over the first 3-5 years of operation, which is not the best solution. Finally, data collection on occupancy (based on people’s count) and GDPR-related concerns were found to pose some privacy concerns in some countries (e.g., Canada), which is still an unsolved issue.

8.4 Conclusions

From an analysis of the interim evidence gained from the experiences and lessons learnt of early adopters of smart-building technologies, it was clear that there is a general lack of open data from real smart-building implementations and widespread agreement on standardisation (e.g., metadata cataloguing, data labelling and interoperability) often induce the adoption of *ad hoc* approaches and proprietary solutions that hamper the exchange and reuse of possibly valuable information. Data quality and collection was the most recurrent issue reported in the case studies collected and analysed as part of Subtask D.1 activities. Such issues may significantly affect several aspects, including the applicability of data-driven algorithms, information extraction and inference making, quality and accuracy of predictions, and ultimately costs.

Limited availability of clear narratives, technical details on real-world implementations, and a need for more clear articulation of the value proposition were identified as factors hindering the implementation of smart-building digital technologies at scale. The conservative industrial structure, limited skill integration and widespread siloed thinking typical of this field were recognised to limit the sharing of know-how and best practices. Similarly, the engagement of occupants and training was deemed essential to allow people to become familiar with the best-practice operation of a new data-driven smart technology and associated benefits. It was recognised that information repositories and positive case studies capturing international perspectives, such as those being developed within Subtask D.1, should be encouraged to drive innovation in data-driven smart buildings. Finally, privacy concerns, cybersecurity, the perception of losing control, and legal implications of novel implementations of data-driven smart technologies in general (e.g., implications of changes to operating agreements) should be fully addressed or refined to foster more confidence in adopting such solutions.

8.5 References

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9. Conclusions

This report has provided a brief overview of the state-of-the-art in the vast and rapidly developing area of Data-Driven Smart Buildings.

Chapter 1 discussed **what a Data-Driven Smart Building is**. The participants in Annex 81 carried out an exercise to identify attributes that are common to Smart Buildings: the "word cloud" shown in Fig. 1.2 shows that "adaptability", "flexibility", "thinking ahead", "learning" were some of the most commonly mentioned features. Further exploration of the concept underscores that a *data-driven* smart building should incorporate two main elements: (1) **real-time** interaction between software and hardware in real-time to deliver value for the operators; (2) "**data pipes"** to ensure data quality, which includes: labelling and context (tagging, benchmarking); a systematic structure for access and discoverability; and provisions to guarantee consent, privacy and cyber-security. After presenting common features of this type of building that make them distinct, a definition emphasizing the "data-driven" aspect was proposed, considering that other individuals and organizations have developed definitions of the concept of Smart Building.

Chapter 2 addressed the topic of **data platforms**. For data to be helpful for any application, it needs to be available somehow on a suitable platform. There are significant challenges regarding the lack of standardization of information flow in the building operation field, especially across the numerous building systems (HVAC, lighting systems, security, etc.). Open access platforms promise to be a solution in this direction. Data "production" significantly depends on the complexity of the control system, which may range from simple local control to advanced SCADA systems, including machine learning and AI features. Furthermore, so that data can be used, it should be made available to potential users: data deployment may range from any format (a simple PDF file containing tables of values) up to easily discoverable, interlinked data. Finally, the concepts of "data swamps" and "data lakes" were compared. In a "data swamp" data is stored in a siloed, fragmented way, is hard to find, is available in a rigid format, and is of rather poor quality; in contrast, in a "data lake", data is clear, well-structured, easy to find, well-explained, easy to access and easy to understand.

Chapter 3 discussed **data information management** strategies. The critical concept of ***metadata*** ("data about data"), presented in Chapter 2, is discussed in depth. So that data can be used in diverse applications, detailed descriptive information about it is required. However, the lack of standardized and precise "tagging" for the building data is one of the core challenges in the field. The problem is further complicated by the unescapable fact that buildings vary enormously, and it is challenging to generalize solutions obtained in one case for other buildings. Moreover, buildings are complex and contain numerous systems and subsystems, but not all the data is essential for a specific application. Finally, buildings are dynamically evolving entities; data must grow with them so that the information obtained remains valid.

Metadata standards for buildings, i.e. systematic methods to describe the variables of a dataset and their ontology (meaning and relationships), are presented and discussed in detail. Some of these standards, which include both open-source and private initiatives, are *Project Haystack*, *Brick*, *RealEstateCore*, and *Google Digital Buildings*. ASHRAE is developing its own metadata standard. The adoption of metadata standards in building operation confronts several significant obstacles: the novelty of the technology and the resulting limited uptake by digital control systems, the multiplicity of standards, and the lack of turnkey solutions. It is pointed out that, in comparison, data management itself is "easy".

The second topic discussed in Chapter 3 was the **integration of data and metadata into existing software platforms**. Again, the heterogeneity of buildings is a challenge but also an opportunity. One source of metadata is provided by building information models (BIMs); while still rarely found and of variable quality, they are the best and most structured representation of buildings. Building operational systems, such as building automation systems (BAS) and energy management systems (EMS), also provide metadata. Still, these descriptions are alphanumeric strings that do not follow a standard format and contain limited information. The metadata extraction from these labels has been investigated using techniques such as direct extraction or translation between ontological representations. Inference-based techniques have been explored to benefit from more unstructured information by learning from human experts, perturbations to better understand which variable responds, relationships between equipment, etc.

Chapter 4 tackles one of the main applications of data for buildings: **data-driven controls**. Model-based predictive control (MPC) is discussed, addressing specifically the creation of models for this application. MPC is a control approach whereby a model of a system is used to predict the result of different control actions. An optimization routine is then used to select the best course of action according to a specific objective, such as energy use, peak electric load, and GHG emissions.

The fundamental step in MPC is the creation of an appropriate, reliable model, which is a "good enough" reflection of the behaviour of a building or one of its systems. As per an informal survey carried out among the participants of the Annex, there was a general agreement that model development is the most time-consuming activity in MPC and one of the main challenges for adopting this technique as a mainstream practice. Models used in control applications are often classified into three categories with somewhat blurry boundaries between them: *white-box* models, developed from fundamental principles (e.g., heat transfer and thermodynamics) and a description of the layout and materials of the building; *black-box* models, providing mathematical correlations between inputs and outputs datasets; and *grey-box* models, a sort of compromise between the first two kinds, in which a simple model with relatively few parameters is calibrated with existing data. In recent years, the availability of large datasets and the development of machine-learning techniques have boosted the utilization of black-box models. Techniques for the creation of grey-box models are discussed in detail. Grey-box models are also a popular option for MPC, but their *system identification* (i.e., the determination of the value of their parameter) can be quite challenging. Reinforcement learning (RL) has also emerged in recent years as a machine-learning concept in which the results of numerous control scenarios are assessed in terms of their performance, and a score (reward/punishment) is attributed to each control strategy. Since RL relies only on data from the results of control scenarios, it is sometimes referred to as a "model-free" method. In the case that not enough data is available, a virtual "gym" (a reliable, general digital twin) can be used to "train" the RL algorithm and assess the performance of different control strategies.

Chapter 5 discussed some technical challenges of deploying data-driven control strategies in a building. The relationship between forecasting and control is discussed in detail, including the need to forecast solar radiation appropriately for short-term responses and implementing outdoor temperature forecasts. This chapter also discusses different approaches to MPC. The most common one is by far "mean value-based" MPC, the simplest method, usually based on an economic objective (economic MPC). Linear quadratic MPC involves other "regularisation" terms that help minimize the impact of the variance of the input signal. One of the challenges mentioned is that multi-zone systems may be difficult to control due to the lack of information about measurements in individual rooms. Distributed MPC is also cited as an alternative approach for multi-zone systems. After presenting an example of MPC applied to a Danish school building, Chapter 5 ends with the presentation of the concept of hierarchical controls using flexibility functions and the *Minimum Interoperability Mechanisms* as the basic information blocks to create an energy market for buildings in the context of energy exchange with the grid, zooming in and out at differentl hierarchical levels.

Chapter 6 thoroughly overviews data-driven fault detection and diagnosis (FDD) in building systems. First, the steps required before FDD can be implemented are described. After data collection and cleansing (which may include imputation methods to insert missing values in incomplete datasets), a pre-processing phase occurs: pre-processing involves feature selection (i.e., which variables are relevant among the thousands available), data scaling, partitioning, etc. Then a baseline, representing "business as usual" operation, is required. It is well known that buildings rarely operate as intended. Therefore, identifying faults requires detecting significant deviations from a baseline (which will be different in heating and cooling modes).

With a clean, pre-processed dataset, and an established baseline, the *fault detection* phase takes place. There is a wide variety of methods for fault detection, which may be classified into three categories: *supervised*, *semi-supervised* or *unsupervised*. In supervised methods, labelled fault data is used along with data under normal operation. In semi-supervised methods, only limited labelled data is available. Finally, in unsupervised methods, no fault labels are required; these methods (clustering algorithms, PCA) are useful for discovering hidden correlations within the data and are the easiest ones to implement.

Fault diagnosis goes one step further. Identifying the source of a fault is often more complex than detecting whether a fault exists. Bayesian network models that use observation to confirm or refute beliefs about the potential cause of a fault are popular. Other methods for diagnosis include "fault-trees" (based on a decision tree and multiple "if statements") and other machine learning methods (SVMs and ANNs). Finally, fault prognosis predicts the likely course of a condition in the system and can be used in predictive maintenance. After reviewing the vast number of systems to which FDD techniques are applied and presenting evaluation metrics for these techniques, the chapter concludes by discussing challenges in this area (such as deployment, scalability, interpretability and cyber security), potential solutions are provided (e.g., validation of FDD, transfer learning and metadata schemas, Bayesian Networks and cyber-resilient control schemes).

Chapter 7 addresses one of the most promising applications of data in buildings: the interaction between buildings and the grid (Building2Grid). Buildings have a significant potential to help regulate the load in the electric grid. In this context, the concept of *energy flexibility* (the capacity of the building to adapt its response to the needs of the grid) is essential. This can occur in two ways: via *direct control* or *indirect control* (by using incentives).

It has been estimated that B2G services can lead to $100-$200 billion in savings in the US. The technology readiness level (TRL) of B2G ranges from 5 to 8. Most technologies are relatively mature. However, significant policy barriers and a lack of business models are substantial challenges. The concept of *flexibility market* has been put forward to address this issue. Commercial initiatives have taken place in Europe and North America for residential as well as commercial and institutional buildings. For example, 4.3 million customers in France have signed up for a variable tariff program for domestic hot water; in the UK, a private energy provider is popularizing spot prices for households linked to smartphone apps; in Central Europe, a a capacity aggregator uses a "virtual power plant" combining the capacities of hundreds of consumers.

As in other applications, apart from the clear challenges with business models, and the lack of a regulatory framework, cybersecurity is one of the primary concerns. In terms of R&D, large-scale pilot projects are needed (including an extensive portfolio of energy end-users

Chapter 8 provided an overview of the methodology developed for collecting **real-world data-driven smart building case studies** and a **summary of interim evidence** gained from the experiences and lessons learnt of early adopters of such technologies. It was recognised that information repositories and positive international case studies exemplars such as those gathered in this work play a significant role in mapping the landscape and provide evidence to reconcile new technologies and their implementation in practice.

It was evident that the exchange and reuse of possibly valuable information from smart-building implementations are often hampered by a general lack of open data and standardisation. Indeed, such issues may have repercussions, for example, on the applicability of data-driven algorithms; information extraction; inference making, quality and accuracy of predictions. Other barriers to the implementation of smart-building digital technologies at scale were identified in not so clear articulation of the value proposition; limited availability of clear narratives, sharing of real-world technical details and know-how; and integration in the current state of practices. Occupants' engagement and training were also deemed essential for people to familiarise themselves with best practice operation of new technology and associated benefits. Finally, novel legal implications stemming from new smart technologies should be fully addressed or refined to foster more confidence in such solutions.