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meta build

D4.1 – META BUILD Digital Twin, data-driven services & apps for smart energy management, 1st version

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Powering the METAmorphosis of BUILDings towards a decarbonised and sustainable energy system

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Preface

The overall vision is to operationalise energy efficiency first principle in the practical context of buildings, towards the decarbonisation of the EU building stock, through: Electrified low-carbon technologies such as heat pumps for the electrification of the building thermal energy demand; Integration of RES & storage; Building digitalisation and intelligence with smart energy management systems. To achieve the 'META BUILD of the building sector', we will develop and demonstrate at TRL 6-8 highly cost-effective, integrated, and replicable solutions (i.e. Heat Pumps coupled with RES and ES systems) for electrifying thermal energy demand in buildings. Social acceptance and strict adherence to energy efficiency measures will be ensured to promote a sustainable, efficient energy use and an affordable pathway to decarbonise the heating demand of the building-sector. A holistic approach addresses challenges throughout the building life cycle, including product manufacturing, energy solution design and engineering, construction, renovation, operation, and maintenance.

META BUILD will deliver:

- KPI-driven assessment methodology & LCA analysis on building electrification.
- Decarbonisation as a service decision support tool; sound Business Models combined with energy efficiency and electrification.
- Advanced HP technologies, PVTs & other RES solutions, thermal & second-life battery storage systems.
- Interoperable framework for electrified ready buildings; Energy management services for RT-monitoring & performance analytics.
- Demand response, grid interaction & flexibility planning tools.
- Pro-active maintenance & controls services.
- Digital Twins for maintaining / enhancing the buildings' performance; Blueprints & policy recommendations for replication & scalability.

Focus will be given on both construction and renovation phases of a building, while META BUILD solutions will be demonstrated and replicated in different types of buildings including 6 Front Runners and 7 Replication Multipliers.

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Participants

ICCS	EREVNITIKO PANEPISTIMIAKO INSTITOUTO SYSTIMATON EPIKOINONION KAI YPOLOGISTON	EL		CARTIF	FUNDACION CARTIF	ES	
EURAC	ACCADEMIA EUROPEA DI BOLZANO	IT		ED	EUROPEAN DYNAMICS LUXEMBOURG SA	LU	
INETUM	INETUM	FR		INETUM ES	INETUM ESPAÑA S.A.	ES	
BLUEPRINT	BLUEPRINT ENERGY SOLUTIONS GMBH	AT		IDM	IDM ENERGIESYSTEME GMBH	AT	
SOZIALBAU	SOZIALBAU GEMEINNUTZIGE WOHNUNGSAKTIENGESELLSCHAFT	AT		HOB	HAUSSERVICE OBJEKTBEWIRTSCHAFTUNGSGMBH	AT	
TUD	TECHNISCHE UNIVERSITAET DRESDEN	DE		UNIZAG	SVEUCILISTE U ZAGREBU, FAKULTET STROJARSTVA I BRODOGRADNJE	HR	
CER	CIRKULARNI ENERGETSKI RESURSI DOO ZA PROJEKTIRANJE I IZGRADNJU ENERGETSKIH POSTROJENJA	HR		HEPT	HEP-TOPLINARSTVO D.O.O.	HR	
GSG	GRADSKO STAMBENO GOSPODARSTVO VELIKA GORICA DOO	HR		GVG	GRAD VELIKA GORICA	HR	
EDF	ELECTRICITE DE FRANCE	FR		SAUTER	SAUTER REGULATION SAS	FR	
KMO	KMO	FR		ENOV CAMPUS	E-NOV CAMPUS	FR	
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ANIMA	ANIMA - FEDERAZIONE DELLE ASSOCIAZIONI NAZIONALI DELL'INDUSTRUSTRIA MECCANICA VARIA ED AFFINE	IT		TECNALIA	FUNDACION TECNALIA RESEARCH & INNOVATION	ES	
ENDEF	ENDEF ENGINEERING SL	ES		CIRCU LI-ION	CIRCU LI-ION S.A.	LU	
EAP	ENERGY AGENCY OF PLOVDIV ASSOCIATION	BG		HELEXIA	HELEXIA CORPORATE	FR	
UNIPassau	UNIVERSITAT PASSAU	DE		THES	DIMOS THESSALONIKIS	EL	
RPR	RIGAS PLANOSANAS REGIONS	LV		FASADA	PRZEDSIEBIORSTWO ROBOT ELEWACYJNYCHFASADA SP ZOO	PL	
GDYNIA	GDYNIA-MIASTO NA PRAWACH POWIATU	PL		VEOLIA	VEOLIA SERVICIOS LECAM SOCIEDAD ANONIMA UNIPERSONAL	ES	
ARTELYS	ARTELYS	FR		RAP	REGULATORY ASSISTANCE PROJECT	BE	
EHPA	EUROPEAN HEAT PUMP ASSOCIATION	BE					

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Executive Summary

The META BUILD project aims to accelerate the decarbonisation of Europe's building sector through an innovative combination of digital technologies, renewable energy solutions, and advanced energy management strategies. With a clear vision for promoting sustainability and energy efficiency, this initiative integrates state-of-the-art heat pump systems, photovoltaic-thermal technologies, and second-life battery storage solutions, emphasizing not only technology advancement but also scalability and replicability in diverse building contexts.

Central to the project is a robust architectural framework that ensures interoperability across various technology enablers and facilitates seamless integration between renewable energy sources, storage systems, and digital services. By leveraging cutting-edge middleware platforms, standardised Application Programming Interfaces, and semantic interoperability tools, the project aims to overcome existing market fragmentation, enabling diverse systems—ranging from heat pumps of varying scales and capabilities to sophisticated battery management systems—to communicate and operate harmoniously. Key digital components, such as Model Predictive Control, Building Energy Management Systems, and Digital Twins, enhance operational intelligence, offering predictive analytics, proactive maintenance, and optimised control strategies that significantly elevate building performance and comfort.

The integration of advanced heat pump technologies—including district-heating-connected heat pumps, MW-scale reversible heat pumps, dual-source/sink units, and monobloc installations—demonstrates the project's capability to address electrification of heating and cooling demands across various scales and climatic conditions. Photovoltaic-thermal systems, including both air-based and direct lamination aluminum absorber technologies, further complement these solutions by simultaneously generating electricity and heat, optimizing energy usage, and facilitating renewable energy integration. The project's use of second-life lithium-ion batteries adds a sustainable dimension, extending battery lifespans and reducing overall environmental impact while ensuring reliability and cost-effectiveness.

META BUILD places significant emphasis on semantic interoperability, recognizing its essential role in achieving seamless data exchange, predictive analytics, and dynamic energy optimisation. The project strategically addresses current limitations related to proprietary standards and fragmented systems through a combination of open standards adoption, comprehensive semantic models, and middleware integration strategies. Moreover, substantial progress has been made in aligning these interoperability frameworks with EU-wide data governance initiatives, ensuring compliance with cybersecurity standards and GDPR requirements.

Looking forward, the project's strategy Prioritises scalability, adaptability, and enhanced integration potential. Plans include broadening the modular design of technologies, refining digital twin capabilities, and further improving predictive control mechanisms. Advanced analytics and automated predictive maintenance systems are expected to substantially improve system efficiency, longevity, and user comfort. By pursuing flexible installation frameworks for renewable systems and promoting open standards and semantic interoperability, META BUILD aims to provide replicable blueprints and actionable policy recommendations for extensive adoption throughout Europe.

Ultimately, META BUILD embodies a comprehensive and transformative approach to smart, sustainable building energy management, combining innovative technologies, digital intelligence, and strategic interoperability frameworks to empower stakeholders across the construction, renovation, and operational phases of the built environment.

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List of Abbreviations

AI	Artificial Intelligence
AHU	Air Handling Unit
API	Application Programming Interface
AWS	Amazon Web Services
BAS	Building Automation System
BDI	Building Digitalisation and Intelligence
BESS	Battery Energy Storage System
BMS	Building Management System
BRP	Balance Responsible Party
BUC	Business Use Case
CAV	Constant Air Volume
CO_2	Carbon Dioxide
CRUD	Create, Read, Update, Delete
CINEA	European Climate Infrastructure and Environment Executive Agency
DaaS	Decarbonisation as a Service
DERA	Data Exchange Reference Architecture
DHN	District Heating Network
DR	Demand Response
DSHP	Dual Source Heat Pump
DSO	Distribution System Operator
DT	Digital Twin
EEM	Empresa de Electricidade da Madeira
EMS	Energy Management System
ESS	Energy Storage System
ESS-VPP	Energy Storage System Virtual Power Plant
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FFR	Fast Frequency Response
FMS	Furnace Monitoring System

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GA	Generic Adapters
HEMS	Home Energy Management System
HP	Heat Pump
HVAC	Heating, Ventilation and Air Conditioning
IoT	Internet of Things
KPI	Key Performance Indicator
MFH	Multi-Family Housing
MPC	Model Predictive Control
PCM	Phase Change Material
PM	Particulate Matter
PV	Photovoltaic
PVT	Photovoltaic-Thermal
RCM	Reliability Centred Maintenance
RES	Renewable Energy Sources
SFH	Single-Family Housing
SoC	State of Charge
SoH	State of Health
SSA	Service Specific Adapters
TE	Technological Enabler
ToU	Time-of-Use
VOC	Volatile Organic Compounds

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1 Introduction

Deliverable D4.1 “META BUILD Digital Twin, data-driven services & apps for smart energy management, 1st version” serves as the foundational document detailing the initial implementation of the META BUILD Digital Twin, along with data-driven services and applications aimed at enabling advanced smart energy management across diverse building contexts. It aligns strategically with the overarching goal of META BUILD to foster a significant reduction in building carbon emissions through digitisation, renewable integration, and innovative service delivery.

1.1 Scope of the document

The purpose of this document is to provide a comprehensive overview of the preliminary META BUILD architectural framework, technological enablers (TEs), integration strategies, and initial digital services designed within the project’s context. It offers an extensive exploration of the capabilities and functionalities of various technologies, specifically focusing on heat pump solutions, photovoltaic-thermal (PVT) systems, second-life battery storage technologies, and digital twin implementations. The document outlines interoperability considerations, identifies integration points, and sets the stage for future technical advancements and validations within the META BUILD framework.

1.2 Connection with other Work Packages

This deliverable is inherently interconnected with other Work Packages (WPs) within the META BUILD project. It closely aligns with WP2 – “Electrified thermal energy demand integrated solutions & demonstration strategy”, which defines system and business use cases (SUCs/BUCs) by providing an architectural foundation that facilitates practical validation. Furthermore, it strongly correlates with WP3 – “Technologies enabling electrification”, incorporating detailed descriptions and advancements of technological enablers that serve as the building blocks of this deliverable's architecture. Simultaneously, WP5 – “Deployment & demonstration in real cases” focuses on demonstration activities benefits directly from the digital twin and data-driven services described herein, whereas WP6 – “Solutions adoption, replication, scalability & exploitation” leverages insights from the documented integration strategies and interoperability outcomes to support policy recommendations and replicability potential. The comprehensive integration approach documented in this deliverable thus fosters synergy across all relevant project activities.

1.3 Structure of the document

The document is structured in a manner that sequentially guides the reader through critical aspects of the initial digital twin and service implementation:

- Section 2 establishes the methodological and architectural foundation, detailing the conceptual approach and mapping it to identified business and technological use cases.
- Section 3 provides a detailed account of technologies enabling electrification, renewable energy integration, and storage solutions, highlighting their structural aspects, interoperability, and future scalability.
- Section 4 focuses on detailed partner-specific contributions and technology-specific analyses, outlining technological progress, integration points, and preliminary interoperability considerations from individual technology providers.

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- The conclusion section summarises key insights, articulates conclusions, and sets forth clear recommendations for next steps and continued technological development within the META BUILD project framework.

2 Unified architectural framework and system integration

This section denotes the methodology and the architecture of the META BUILD framework that encapsulates all the technologies within the project.

2.1 Methodology

The methodology that was followed to derive the architecture of the META BUILD project is based on the categories that the project provides, which are namely 1) the Decarbonisation technologies which are split into the electric load (i.e. PVs, second-life batteries) and the thermal load technologies (i.e. Heat Pumps (HPs), PVTs), 2) the Enablers for the Services, 3) the Service layer. Additionally, the services within the project are validated in the Business Use Cases (BUCs) that are identified and detailed in deliverable D2.1 – “Enabling conditions & consolidation factors for building electrification, 1st version” [1]. Then, the services are also adopted by the end users and the buildings that they are residing at. All these categories are illustrated in Figure 1.

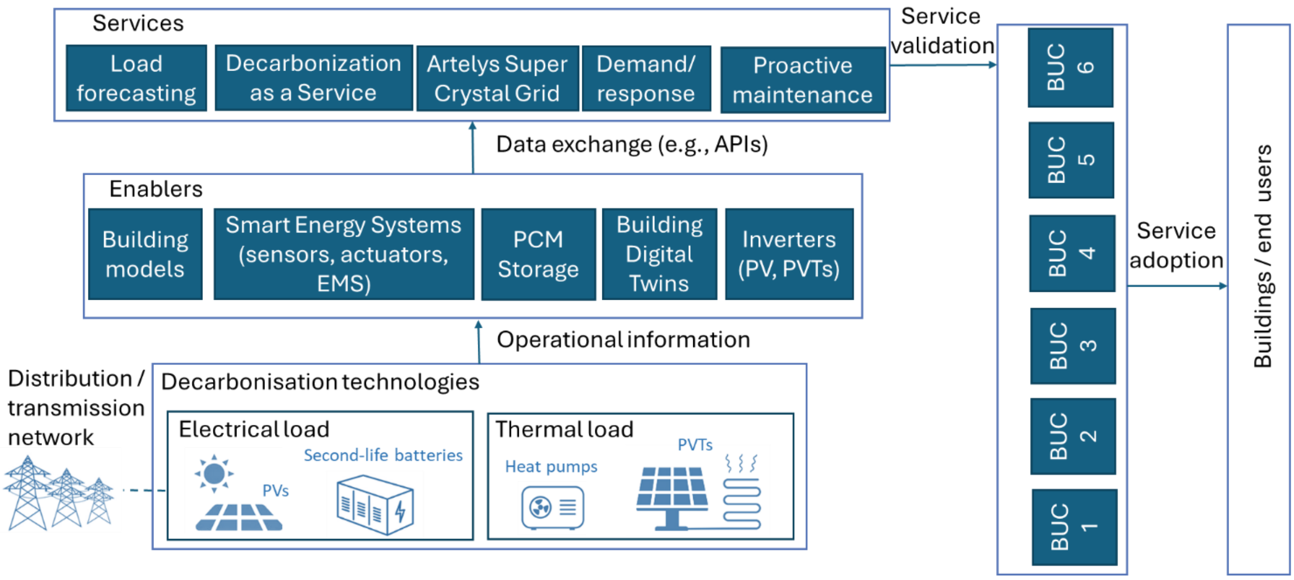

Figure 1 Methodology for META BUILD framework definition.

Specifically, the categories were derived from the use of hardware-based solutions as HPs and PVTs for electrifying the thermal load and achieving decarbonisation as well as the RES technologies as the PVs and the second-life batteries used for the electrical load. Then, and coupling those technologies as well as their operational information with enablers that allow to provide decarbonisation services within META BUILD. The enables are using data exchange methods, as Application Programming Interfaces (APIs) to send data towards the service layer. Within the service layer, the META BUILD services are being developed as well as validated in BUCs and the associated KPIs. Upon their validation, they are adopted in buildings and by end-users, which are the main stakeholders within the project.

2.2 META BUILD architectural framework

The architectural framework is using the Technological Enablers and the BUCs from the methodology of the section 2.1 to provide a framework that will include all the technological innovations within the META BUILD project. This framework including all the TEs as well as the interconnections and coupling of the technologies is depicted in Figure 2.

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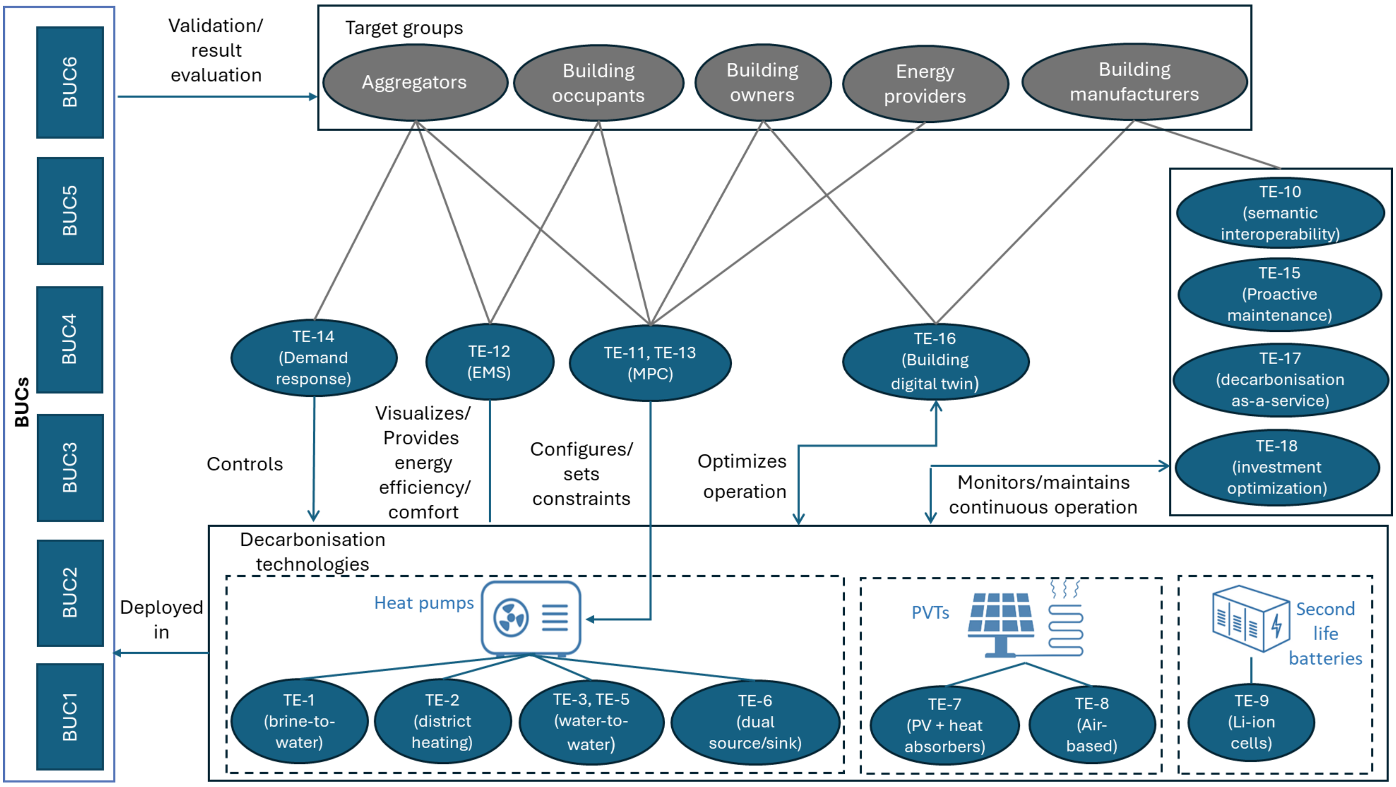

Figure 2 Architectural framework of the META BUILD project

The META BUILD architecture contains the decarbonisation technologies including three main categories 1) the HPs, 2) the PVTs and 3) the second life batteries. Within the first category the HPs that are developed within the project are depicted including TE-1 (brine-to-water), TE-2 (district heating), TE-3/TE-5 (water-to-water), and TE-6 (dual source/sink). The second category includes the PVTs, which is composed of the TE-7 (PVs that also include heat absorbers) as well as the TE-8 (air-based systems). Then, the third category includes the second-life batteries provided by TE-9 (lithium-ion cells). These categories are developed within WP3 – "Technologies enabling electrification" and are further explained in D3.1 – "Technologies for enabling electrification and business models, 1st technology release" [2] as well as in Section 3 of this deliverable.

The decarbonisation technologies within the META BUILD project interact with open-energy management services and key enabling components. These interactions define how various technological enablers contribute to the overall architecture. The framework organises these elements into two main functional categories based on their roles:

Technology Enablers with Direct Interaction with One or Two Technologies

This group consists of enablers that primarily focus on specific decarbonisation technologies:

- TE-14: Demand Response Service:
  - Adjusts and responds to external energy demands dynamically.
  - Helps balance grid demand by shifting loads based on pricing signals or renewable energy availability.
- TE-12: Energy Management System (EMS):
  - Provides visualisation and monitoring of energy consumption.
  - Optimises energy efficiency and comfort levels for building occupants.
- TE-13: Model Predictive Control (MPC) Module:

  - Configures and applies constraints to heat pump operations.
  - Ensures optimal efficiency by adapting operations based on real-time building conditions.
- TE-16: Building Digital Twin:
  - Creates a digital representation of the building.
  - Optimises the operation of decarbonisation technologies through simulation and predictive analytics.

Technology Enablers Supporting Multiple Services Across the System

This second group includes enablers that facilitate broader interoperability, maintenance, and integration across multiple decarbonisation technologies and services:

- TE-10: Semantic Interoperability Enabler:
  - Ensures seamless data exchange between various services and components within the META BUILD framework.
  - Facilitates communication between different platforms and technologies.
- TE-15: Proactive Maintenance System:
  - Detects and predicts potential faults in decarbonisation technologies.
  - Enables early-stage identification of performance issues to minimise downtime and optimise system longevity.
- TE-17: Decarbonisation-as-a-Service (DaaS):
  - Provides data-driven recommendations to building owners on optimizing decarbonisation strategies.
  - Supports decision-making for cost-effective and sustainable building energy transitions.
- TE-18: Artelys Crystal Super Grid:
  - A multi-energy system modelling platform integrated within WP6 – "Solutions adoption, replication, scalability & exploitation".
  - Evaluates the impact of META BUILD solutions on the electricity grid and supports energy system planning.

The services developed within META BUILD will be validated through the **project's key target groups, w**hich include:

1. Aggregators – Entities that manage flexibility services in energy markets.
2. Building Occupants – End-users who directly interact with energy systems.
3. Building Owners – Decision-makers responsible for implementing energy management strategies.
4. Energy Providers – Companies supplying electricity, optimizing energy distribution.
5. Building Manufacturers – Stakeholders involved in the production and integration of smart building solutions.

These services will be tested and assessed as described in D2.1 – "Enabling conditions & consolidation factors for building electrification, 1st version" [1]. The validation process will be conducted against a predefined set of Key Performance Indicators (KPIs), ensuring that the technologies and services provide measurable benefits. Moreover, the results of these validations will refine the META BUILD framework and continuously improve the integration of decarbonisation technologies and enabling services.

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Additionally, the META BUILD framework includes Technology Enablers that focus on monitoring, maintaining, and optimizing the continuous operation of decarbonisation technologies. These enablers play a crucial role in ensuring interoperability, predictive maintenance, and decision-making support:

- TE-10: Semantic Interoperability Enabler:
  - Facilitates seamless data exchange across different services and components.
  - Ensures smooth integration of various technologies within the META BUILD framework.
- TE-15: Proactive Maintenance System:
  - Detects and predicts faults in key decarbonisation technologies.
  - Provides early-stage maintenance interventions to improve system reliability.
- TE-17: Decarbonisation-as-a-Service:
  - Acts as a recommendation engine for optimizing CO2 reduction strategies.
  - Supports building owners in making data-driven decisions regarding energy efficiency.
- TE-18: Artelys Super Crystal Grid:
  - A multi-energy system modelling platform used within WP6 – “Solutions adoption, replication, scalability & exploitation”.
  - Evaluates the broader impact of META BUILD solutions on electricity grid stability.

The META BUILD services are validated against Business Use Cases, which are outlined in D2. 1 – “Enabling conditions & consolidation factors for building electrification, 1st version”. This validation ensures that each service meets predefined Key Performance Indicators and effectively supports relevant stakeholders, including:

1. Aggregators – Manage energy flexibility and market interactions.
2. Building Occupants – Engage with smart energy solutions at a user level.
3. Building Owners – Implement and oversee energy management strategies.
4. Energy Providers – Ensure optimised grid operations and market stability.
5. Building Manufacturers – Contribute to the deployment of smart building technologies.

Validation outcomes will feed back into the META BUILD framework, allowing continuous refinement and enhancement of decarbonisation technologies and enabling services to maximise efficiency and impact.

2.3 META BUILD minimum services data requirements

As part of T4.2 “Value-added services co-design & modelling framework for data-driven services”, we have compiled key data to facilitate precise service integrations and ensure seamless project execution. To support this effort, a structured template was developed to systematically capture the minimum data requirements for META BUILD Services. The objective of this work is to confirm data availability, identify potential gaps, and establish a comprehensive understanding of the resources necessary for effective implementation.

The template is designed to encompass both static and dynamic data requirements, ensuring a structured and consistent approach to data collection. It includes the following key fields:

- Data Type: Specifies the nature of the data (e.g., numeric, text).
- Unit of Measurement: Defines the applicable unit for each data point (e.g., kilowatt-hours, degrees Celsius).

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- Level: Indicates the level at which the data is collected (e.g., whole building, individual apartment, specific equipment such as HVAC or lighting systems).
- Time Interval: Specifies the duration over which the data is collected (e.g., August 2023 to August 2024).
- Best Case Granularity: Defines the most detailed level of data granularity preferred (e.g., per minute).
- Worst Case Granularity: Identifies the least detailed level of granularity acceptable for analysis (e.g., per hour).

The table found on Annex A, presents the consolidated results based on input from service providers gathered in the context of this task. This overview highlights the collected data, identifies any gaps in availability, and serves as a foundation for further analysis and integration effort.

2.4 Integration strategies: Middleware approach

META BUILD Reference Architecture design relies heavily in a governance "integration middleware" aiming to offer a specific services and functionalities that facilitate seamless connectivity between platforms and data sources. This capability can be enhanced to include data transformation, routing, discoverability, and context management. By simplifying complex integration processes, middleware allows demos and technical partners to concentrate on business logic and data valorisation, rather than dealing with the technical intricacies of system interoperability. The aforementioned middleware is based on the H2020 Interconnect project's [68] interoperable core, which is used to create a semantic interoperability framework for local energy grids and RES production, enabling seamless integration and peer-to-peer trading of energy assets. This middleware core in conjunction with Data Space architecture logic to deliver advanced smart energy management services and Digital Twins which are secure and trusted toward the end goal of complete building decarbonisation through electrification technologies.

Part of the above middleware are mainly the semantic interoperability enables and respective API endpoints & gateways which adhere to a set of standards for minimum interoperability, in alignment with Semantic Interoperability Framework (SIF) and the Data Space connectors [97]. This development builds on interoperability matrix for energy management identified in the H2020 X-FLEX project [73], facilitating the optimum combination of decentralised flexibility assets, both on the supply side and on the demand side, including power-to-heat/cold/gas, batteries, demand response. From a pure technical perspective META BUILD uses an intermediary software layer that provides access to services, enables integration and interoperability and provides secure authentication, logging, and potentially monitoring features.

2.5 META BUILD Use Cases – Connection with architectural framework

The META BUILD architectural framework has been structured to ensure an interoperable and scalable integration of decarbonisation technologies and advanced energy management services. The framework provides a standardised approach for coupling Technological Enablers with Business Use Cases, ensuring that pilot demonstrations across different climatic zones and building typologies leverage a unified methodology while addressing location-specific challenges. The following sections analyse how each BUC aligns with the architectural framework, focusing on TE integration, system-level interactions, and validation objectives.

Use Case 1 – Austria: Extensive Retrofitting of a Central-European Residential Building

The Austrian pilot focuses on the electrification and deep energy retrofit of a 1983-built residential complex by replacing gas-based heating systems with high-efficiency R290 brine-to-water heat pumps (TE-1) and incorporating photovoltaics (PV) and second-life battery storage (TE-9). This aligns with the META BUILD architecture, where decarbonisation technologies (TE-1, TE-9) interface with building modelling tools (TE-11) and MPC-based control strategies (TE-13) to optimise heating, energy storage, and grid interaction. The architectural framework supports this use case by enabling real-time operational data exchange through an Energy Management System, ensuring semantic interoperability (TE-10) and facilitating predictive control strategies for optimizing heat pump operation and storage utilisation. The validation within BUC-P1 will focus on energy cost reduction, CO_2 emissions minimisation, and enhanced user comfort.

Use Case 2 – Croatia: Retrofitting Residential Buildings Connected to District Heating Network

The Croatian pilot integrates district-heating-connected heat pumps (TE-2) with air-based photovoltaic-thermal technology (TE-8) to enhance building efficiency and demand-side flexibility. The architectural framework incorporates TE-15 (Operation, Control & Proactive Maintenance) and TE-17 (Decarbonisation as a Service - DaaS), ensuring data-driven decision-making for optimised heating schedules, demand response, and load balancing. Through semantic interoperability (TE-10) and multi-energy modelling (TE-18 – Artelys Crystal Super Grid), this use case showcases a scalable integration approach, allowing real-time interactions between EMS, the district heating network (DHN), and smart metering infrastructure. The pilot will validate how aggregated flexibility and optimised heating profiles contribute to reduced fossil fuel dependency, cost savings, and improved energy resilience.

Use Case 3 – France: Retrofitting an Office Complex in a Historic Peri-Urban Area

The French pilot focuses on retrofitting the KMØ office complex, integrating MW-size reversible heat pumps (TE-3), battery storage (TE-9), and advanced EMS functionalities. A core element within the architectural framework is the deployment of Digital Twin technology (TE-16) to enable real-time monitoring, optimisation, and scenario-based control of energy assets. Additionally, semantic interoperability enablers (TE-10) ensure data harmonisation across Building Management Systems (BMS) and the existing IT infrastructure. The DaaS model (TE-17) will provide data-driven recommendations for energy optimisation, ensuring heritage conservation while electrifying the energy demand of the building. The pilot's integration into the META BUILD framework will validate scalability strategies for industrial-scale decarbonisation efforts while balancing historical preservation, sustainability, and economic feasibility.

Use Case 4 – Greece: Comprehensive Decarbonisation and Demand Response for Residential Buildings

The Greek pilot aims to transform residential buildings into active energy nodes through a Home Energy Management System (HEMS) that optimises heat pump operations (TE-4), local PV generation (TE-7, TE-8), and energy storage (TE-9). The architectural framework integrates real-time energy data analytics, demand response (TE-14), and digital services (TE-12 - Enhancing Comfort & Energy Performance) to dynamically adjust Heating, Ventilation & Air Conditioning (HVAC) operation, implement load-shifting strategies, and maximise self-consumption. The semantic interoperability layer (TE-10) enables seamless data exchange between smart meters, IoT sensors, and energy market platforms, allowing real-time flexibility planning while supporting pricing mechanisms and user-driven energy strategies. This BUC will validate the efficiency of dynamic energy scheduling, ensuring cost savings, grid stability, and increased user awareness of energy consumption patterns.

Use Case 5 – Italy: Comprehensive Renovation of a Multifamily Building with Air-to-Water Heat Pumps and PCM Storage

The Italian pilot demonstrates deep energy renovation by integrating R290 monobloc air-to-water heat pumps (TE-5) with thermal storage and phase change material (PCM) technology (TE-9) to optimise heating and

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cooling loads. The META BUILD architecture ensures that MPC-based control strategies (TE-13) and DaaS functionalities (TE-17) facilitate predictive operation and intelligent energy scheduling. A key enabler within the framework is semantic interoperability (TE-10), which ensures efficient data management between Building Management Systems, HVAC systems, and EMS platforms. The Artelys Crystal Super Grid (TE-18) further enhances multi-energy system modelling, allowing for strategic investment planning and resource allocation. The validation process will focus on minimizing energy mismatches, optimizing user comfort, and assessing economic feasibility for large-scale adoption of energy-efficient building retrofits.

Use Case 6 – Spain: Implementation of Dual Source/Sink Heat Pumps and PVT Systems

The Spanish pilot integrates Dual Source/Sink Heat Pumps (TE-6) with PVT systems (TE-7) and Digital Twin technology (TE-16) for real-time optimisation of energy usage in TECNALIA's headquarters. The architectural framework ensures that these decarbonisation technologies interact seamlessly with multi-layered energy management systems, leveraging predictive control strategies (TE-15 - Proactive Maintenance) and market-based optimisation tools (TE-17 - Decarbonisation as a Service, TE-18 - Artelys Crystal Super Grid). By embedding semantic interoperability (TE-10), the pilot ensures a unified approach for managing electricity demand, indoor environmental quality, and system-wide efficiency. The Digital Twin serves as an advanced decision-support system, enabling data-driven performance evaluation, operational fine-tuning, and cross-platform integration. The BUC validation will assess the scalability of smart control mechanisms and data-sharing frameworks for optimised heating and cooling strategies.

Final Considerations

Each META BUILD BUC validates specific components of the architectural framework, ensuring that Technological Enablers are seamlessly integrated, interoperable, and adaptable across different building typologies, climatic conditions, and operational environments. The framework's emphasis on decarbonisation, semantic interoperability, and predictive control facilitates scalable deployment models, aligning with project-wide objectives for smart energy management and sustainable building transformation.

2.6 Recommendations for refinement and scalability

Generally, when designing a Reference Architecture, we need to consider a future refinement and scaling process. This means that an architectural model should be able to be optimised for better performance, flexibility, maintainability, and scalability. The enhancement of META BUILD's RA will need to focus on the following key areas from a theoretical perspective:

- Break monolithic software components into microservices to enhance maintainability and deployment flexibility.
- Adhere to a modular approach developing software components.
- Apply service design leveraging RESTful APIs with versioning strategies to ensure backward compatibility.
- Implement API gateways for authentication, rate limiting, and monitoring.
- Reference Architecture relies on the adoption of standardised protocols (e.g., Open API for APIs, OAuth2 for authentication).
- Security by design.
- Enable Role Based Access Control (RBAC), and audit logging.
- Deployment takes into consideration auto-scaling.
- Implement read replicas, sharding, and caching to distribute database load.

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- Use NoSQL databases (e.g., MongoDB, DynamoDB) for high-velocity, unstructured data.
- Event-Driven and Asynchronous Processing.
- Use message queues for Data integration and ingestion (e.g., Kafka, RabbitMQ) to handle high-throughput workloads asynchronously.

As META BUILD progresses, the Reference Architecture (RA) must evolve to support increasing complexity, integration needs, and scalability. The refinement process should ensure a robust, flexible, and interoperable system that accommodates future extensions in digital services, energy management, and building decarbonisation strategies. Given the Minimum Service Data Requirements (Section 2.3), which outline key dependencies on data availability, granularity, and service interactions, the following enhancements are recommended.

Transition to Microservices & Modularisation

- The RA should transition from monolithic implementations toward a microservices-based architecture, where each service (e.g., predictive control, optimisation, and digital twin modelling) operates independently and can be deployed, scaled, and maintained without affecting other components.
- Aligning with data granularity needs: Microservices should be designed to accommodate different data granularity requirements, from minute-level predictive control data to hourly/daily energy reports.

Service-Oriented Architecture & API Interoperability

- To ensure seamless integration, all service interactions should leverage RESTful APIs, standardised with Open API specifications to maintain compatibility across different service providers and platforms.
- API versioning should be enforced to ensure backward compatibility, particularly for services handling aggregated load forecasting, device-level control, and predictive analytics.
- Interoperability across energy systems: APIs must support heterogeneous data sources (smart meters, BMS, heat pumps, storage, RES generation) through semantic mappings for effective communication.

Secure & Scalable Data Management

- Auto-scaling and distributed processing should be adopted to handle the growing volume of real-time and historical energy data.
- Database enhancements:
  - NoSQL solutions (e.g., MongoDB, DynamoDB) should be explored for high-frequency data storage (e.g., real-time EMS readings, predictive maintenance logs).
  - Relational databases (PostgreSQL, MySQL) should be used for structured datasets requiring high integrity (e.g., service configurations, business models, historical analysis).
- Data caching & efficient querying: Implement read replicas, sharding, and in-memory caching (Redis, Memcached) to enhance response times for high-demand services, especially demand-response models and optimisation algorithms.

Event-Driven & Asynchronous Processing for Real-Time Insights

- Given the real-time energy monitoring and predictive service requirements, event-driven architecture should be adopted:

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- Message queues (Kafka, RabbitMQ) will facilitate asynchronous processing, ensuring smooth data ingestion from Distributed Energy Resources (DERs), IoT sensors, and user feedback loops.
- Event streaming will support real-time updates for MPC-based control services, grid interaction mechanisms, and forecasting models.

Enhanced Security, Compliance & Role-Based Access Control (RBAC)

- Security by design should be enforced, integrating:
    - OAuth2/OpenID Connect for secure authentication.
    - RBAC and fine-grained access controls for user roles (e.g., energy managers, building operators, tenants).
    - Audit logging and real-time anomaly detection for cybersecurity resilience.
- Data privacy compliance (GDPR, energy market regulations): Ensure that personal and operational data is managed under strict data governance policies, supporting anonymisation where required.

Edge Computing & Decentralised Energy Management

- To minimise data transmission latency, edge computing should be incorporated, enabling:
    - On-site processing for energy optimisation algorithms and real-time energy scheduling.
    - Decentralised intelligence in building controllers, heat pumps, and energy storage systems.
- Integration with building-level EMS should facilitate distributed decision-making and reduced dependency on cloud latency.

These recommendations directly support the integration and scalability of the services described in Minimum Service Data Requirements (Section 2.3) by ensuring efficient data flow, interoperability, security, and real-time processing capabilities. By adopting modular microservices, enhancing API compatibility, improving data storage strategies, enforcing security measures, and leveraging event-driven architectures, the META BUILD ecosystem can efficiently scale to accommodate future advancements in digital energy services, predictive analytics, and demand-response strategies.

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3 Technologies enabling electrification & integrating RES & Storage

3.1 Overview of Technology Enablers, Roles and Contributions

The technological enablers integrated within the META BUILD project play a central role in promoting electrification, renewable energy sources (RES), and energy storage solutions, significantly contributing to the decarbonisation of the built environment. Among these technologies, heat pumps represent a fundamental element, ranging from large-scale applications such as reversible MW-size heat pumps suitable for substantial office complexes, down to smaller-scale units such as brine-to-water or air-based residential solutions. These heat pump systems leverage advanced refrigerants like R290 and dual source/sink capabilities, greatly improving energy efficiency and adaptability to various climatic and building contexts. Another notable advancement is the deployment of photovoltaic-thermal systems, which come in air-based and direct lamination aluminium absorber configurations, offering both electrical generation and thermal recovery, thus enhancing overall energy performance in diverse architectural applications.

Additionally, the project incorporates innovative energy storage technologies, prominently featuring second-life lithium-ion batteries repurposed from electric vehicles. These batteries extend the lifecycle of existing energy storage solutions, providing substantial cost benefits and sustainability improvements. Their integration is particularly advantageous in balancing intermittent RES generation, allowing the effective storage of daytime solar energy to offset peak evening loads, thus minimizing energy costs and grid dependency. Collectively, these technologies provide an expansive set of tools enabling META BUILD to significantly improve energy management practices, support a dynamic approach to load balancing, and facilitate the adoption of decarbonisation strategies within residential, commercial, and industrial sectors alike.

Beyond energy generation and storage, embedded digital management solutions such as model predictive control and advanced Building Energy Management Systems ensure optimal performance and user comfort by intelligently managing building energy flows based on predictive analytics and real-time data. Digital twin technologies also play a pivotal role by creating virtual replicas of physical assets, allowing for predictive maintenance, real-time performance optimisation, and comprehensive scenario planning. These capabilities collectively enrich the operational effectiveness of building energy management, substantially reducing carbon footprints while increasing resilience against fluctuating energy prices.

3.2 Structural Design, Components and Integration Approaches

From a structural perspective, each technological enabler within META BUILD incorporates several critical components carefully designed to interact seamlessly within the overall architectural framework. Heat pump solutions are engineered with fundamental mechanical and electrical elements including compressors, condensers, evaporators, expansion valves, and various sophisticated sensors that monitor parameters like temperature, pressure, mass flow, and electrical power. Safety during testing, implementation and deployment is considered top priority. For example, all safety-sensitive components are mounted on robust, vibration-damping frames and encased within protective enclosures, ensuring durability and ease of integration within residential or commercial settings. Complementing this hardware is embedded control firmware, which enables real-time operational management including compressor modulation, expansion valve regulation, and fault detection.

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For effective user interaction and digital system integration, a variety of communication interfaces and proprietary cloud-based services have been adopted widely. These interfaces support detailed operational monitoring and remote configuration through intuitive user interfaces, such as touchscreen displays, enhancing user-friendliness and operational clarity. Within larger building complexes, specialised building energy management hardware modules, such as zone modules for room-level temperature control and heat distribution management components, facilitate precise thermal control, thereby increasing system efficiency and occupant comfort. Integration with complementary systems such as photovoltaic-thermal arrays, second-life battery storage, and energy management platforms further highlights the robust and flexible architecture of META BUILD, allowing technologies to support and enhance each other's performance.

Energy storage systems specifically designed around second-life lithium-ion batteries are structurally integrated with advanced battery management systems, grid-forming inverters, and comprehensive safety mechanisms. These systems ensure seamless energy flow and efficient utilisation of stored energy, particularly during peak demand periods. Furthermore, specialised PVT configurations, both air-based and aluminium absorber types, integrate structurally with existing roofing solutions, using simple yet effective airflow or heat-absorbing mechanisms to enhance the energy-harvesting potential without significantly altering building aesthetics or structure.

3.3 Interoperability Considerations and Initial Technical Insights

Interoperability emerges as a critical aspect within the technological enablers implemented in META BUILD, primarily due to the diverse range of systems involved and the necessity for seamless integration and communication. Preliminary findings indicate the need for standardized interfaces in the battery-inverter interactions, the heat pump configuration and control, and various web-based interfaces for real-time data logging and remote monitoring. However, current interoperability often faces challenges stemming from proprietary communication standards, especially observed in the interfaces of heat pump management systems. Efforts are ongoing to explore and potentially adopt more open communication standards that could enhance integration capabilities across different manufacturers and system providers.

Furthermore, advancements in semantic interoperability have been identified as crucial for achieving long-term goals, such as integrated building management systems capable of advanced predictive analytics and autonomous decision-making. Initial research and experimentation within META BUILD indicate that while basic hardware interfaces and simple data exchanges have been successfully established, achieving full semantic interoperability requires further exploration and standardisation efforts. Specifically, the project identifies opportunities for improving the integration of air-based PVT systems with other HVAC technologies, aiming to enhance both physical and digital interfacing to maximise system efficiency.

Additionally, second-life battery systems demonstrate robust preliminary interoperability outcomes, especially regarding their compatibility with standardised inverter technology and associated safety mechanisms. This compatibility is critical for enabling reliable and secure integration within residential and commercial applications, further facilitating the flexible use of renewable energy sources. Moving forward, META BUILD plans to leverage these preliminary findings to enhance interoperability capabilities across all technological enablers, ensuring comprehensive and flexible integration into a unified and effective architectural framework.

3.4 Future Development, Scalability, and Enhanced Integration Potential

Considering the promising technological enablers outlined above, META BUILD has already established a robust foundation for further development and scalability. Future efforts are anticipated to focus extensively on enhancing system modularity and interoperability, particularly leveraging open standards to facilitate

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seamless integration across diverse technology providers and component manufacturers. Efforts to standardise communication interfaces, such as open APIs, represent important steps forward. These initiatives are expected to significantly streamline integration processes, allowing diverse technologies—ranging from advanced heat pumps and second-life battery storage systems to photovoltaic-thermal solutions—to interconnect more effortlessly, maximizing operational synergy and enhancing collective performance.

Moreover, the further evolution of digital twin technologies and predictive control methodologies, such as Model Predictive Control, is anticipated to bring considerable advancements in operational efficiency and decision-making. Enhanced capabilities in real-time analytics and automated predictive maintenance will ensure optimised performance, prolonged equipment life, and minimised operational costs, reflecting positively on the total cost of ownership and the overall sustainability of the systems involved. These digital tools will become increasingly vital, not only for advanced system operation but also for facilitating scalability by providing clearer guidelines, performance validation, and precise operational recommendations for replicating successful installations across diverse contexts.

The use of second-life lithium-ion batteries represents another significant area for further exploration, especially in terms of scaling and replication potential. Their demonstrated compatibility with standardised inverter technology and existing grid infrastructure provides a solid basis for broader deployment. Further research in battery health monitoring, lifetime modelling, and enhanced safety protocols could dramatically increase their attractiveness for large-scale residential and commercial adoption. Developing effective regulatory frameworks and incentivizing such circular economy initiatives will be essential to unlocking this potential fully.

Additional efforts are also expected to target the flexible and modular design of PVT solutions, ensuring that future installations can easily adapt to varied architectural configurations and environmental conditions. By developing flexible installation frameworks, enhancing thermal absorption materials, and optimizing airflow dynamics, future PVT systems are expected to exhibit improved energy harvesting efficiencies and wider architectural integration potential. These efforts will ultimately facilitate broader market acceptance and scalability, enabling easier retrofitting of existing building stocks and integration into new construction practices.

Ultimately, META BUILD's forward-looking strategies emphasise the necessity of achieving not only physical integration and operational interoperability but also semantic interoperability. Future developments could increasingly explore knowledge-based integrations, data federation, advanced inferencing, and machine-learning-based analytics, enabling dynamic and intelligent energy management capabilities that exceed current market offerings. This aspirational vision aligns closely with META BUILD’s strategic objectives of creating scalable, robust, and adaptable technology ecosystems that effectively address both current and emerging challenges in building electrification, renewable integration, and sustainable energy storage.

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4 Building Digitalisation and Intelligence enhancing technologies

4.1 Semantic interoperability enablers for energy management, flexibility planning and effective RES assets integration

4.1.1 Overview

Semantic interoperability is a critical enabler for seamless integration of RES, energy management platforms, and demand-side flexibility tools within the META BUILD framework. Achieving an interoperable and standardised data exchange mechanism ensures optimal coordination of distributed energy resources (DERs), grid-responsive demand, and predictive energy analytics.
This chapter outlines the state-of-the-art methodologies, frameworks, and technologies enabling semantic interoperability. It builds on prior EU-funded projects such as ENERSHARE [65], OneNet [3], and InterConnect [68] to define a common energy data space that allows different systems to communicate effectively while ensuring security, scalability, and compliance with regulatory frameworks such as GDPR and cybersecurity standards.
The success of semantic interoperability in energy management hinges on accurate data harmonisation, standardised data models, and cross-domain integration. Traditional energy management solutions often operate in silos, resulting in inefficiencies and an inability to leverage real-time market and operational insights. META BUILD addresses these gaps by ensuring semantic coherence among energy systems, bridging the communication divide between building management platforms, grid operators, and end users.

4.1.2 Starting status and description

The META BUILD platform relies on various energy assets (heat pumps, second-life batteries, photovoltaic thermal systems) and services (building energy management, demand response, predictive maintenance) that require standardised, interoperable, and context-aware data exchange.

META BUILD also builds upon the foundational work in semantic interoperability from previous projects such as ENERSHARE [65] and OpenDEI [66]. These initiatives have laid crucial groundwork for the development of interoperable energy data spaces and standardised architectures for digitizing European industry.

ENERSHARE, funded under the Horizon Europe program, aims to develop the first Common European Energy Data Space. This project focuses on creating a Decentralised and federated data space that enables secure and sovereign data sharing across the energy sector. ENERSHARE's approach includes:

- Development of a common semantic model for energy data, building on existing standards and ontologies.
- Implementation of data sovereignty and security measures to ensure compliance with GDPR and other regulations.
- Creation of a governance framework for the energy data space, addressing both technical and organisational aspects.

The OpenDEI project has worked on aligning reference architectures, open platforms, and large-scale pilots in digitizing European industry. Its contributions to the energy sector include:

- Definition of a reference architecture for energy data spaces, promoting interoperability and standardisation.
- Exploration of data-driven business models in the energy sector, highlighting the potential for new services and applications.
- Development of guidelines for implementing digital platforms in the energy domain, addressing challenges such as data quality, privacy, and integration of legacy systems.

Building on these foundations, the current state of the art in META BUILD includes:

- Deployment of IoT sensors in pilot buildings for real-time data collection on energy usage, indoor air quality, and environmental parameters.
- Development of predictive analytics for energy demand forecasting, pricing trends, and renewable energy generation predictions.
- Testing of AI-driven algorithms that dynamically adjust HVAC and lighting systems to balance comfort and energy efficiency.
- Evaluation of integration challenges across various sensor platforms and energy systems to inform future standardisation efforts.

4.1.3 Challenges and Constraints

META BUILD starts from the following challenges and constraints that are going to be addressed during design and development of tools and their deployment in pilot sites:

4.1.3.1 Heterogeneous Data Sources

The META BUILD platform integrates multiple energy assets, including heat pumps, battery storage systems, photovoltaic-thermal panels, and building energy management systems. These systems use diverse data formats and protocols, leading to interoperability issues. The lack of common metadata structures across pilot sites hinders data harmonisation [4].

A major challenge is the coexistence of legacy energy management systems and modern smart devices. Legacy systems often use proprietary data formats that are incompatible with new-generation IoT devices and cloud-based energy platforms. This discrepancy necessitates the development of a unified data translation layer that standardises data exchange between different stakeholders in the energy ecosystem.

4.1.3.2 Integration Complexity

Many existing Building Automation Systems (BAS) rely on proprietary communication protocols, making cross-platform interoperability challenging. Middleware solutions, such as ontology-based data mapping, are needed to unify data exchange between legacy systems and modern IoT-based solutions [5].

Integration complexity is further exacerbated by variations in regulatory compliance across European markets. Countries have different approaches to data privacy, market operation, and consumer protection, all of which affect the seamless deployment of a pan-European interoperable energy data space.

4.1.3.3 Scalability and Adaptability

Semantic models must be scalable to accommodate both new and existing buildings, ensuring compatibility across different market conditions and regulatory environments [6]. Scalability challenges emerge when integrating thousands of IoT devices, each with unique data structures and processing requirements. The solution requires a flexible and modular interoperability architecture capable of dynamic expansion without compromising system efficiency.

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4.1.3.4 Security and Compliance

Interoperability frameworks must comply with GDPR and cybersecurity regulations. Secure data exchange mechanisms (analysis will consider Attribute-Based Encryption (ABE) and Privacy-Preserving Federated Learning (PPFL) [7] however previous project experiences for secure data exchange will be utilised based on existing solutions). Security considerations will also address cyber threats, and unauthorised access in distributed energy environments.

4.1.3.5 Real-Time vs. Batch Processing

Semantic interoperability solutions must support both real-time data exchange for energy flexibility and batch analytics for historical performance assessments. An efficient Event-Driven Architecture (EDA) with support for publish-subscribe messaging patterns are typically needed [8]. The ability to process and analyse real-time energy demand signals, while maintaining the ability to perform trend analysis and predictive modelling, is essential for optimal energy efficiency and cost savings.

Data exchange governance elements per SGAM interoperability layers			
Business layer	**Function layer**	**Information and Communication layer**	**Component layer**
1. Data governance business case	4. Data ownership governance	7. Data vocabulary governance	8. Data platforms
2. Orchestrated data governance	5. Data access governance		9. Interfaces
3. Rules and norms	6. Data security governance		10. Repositories

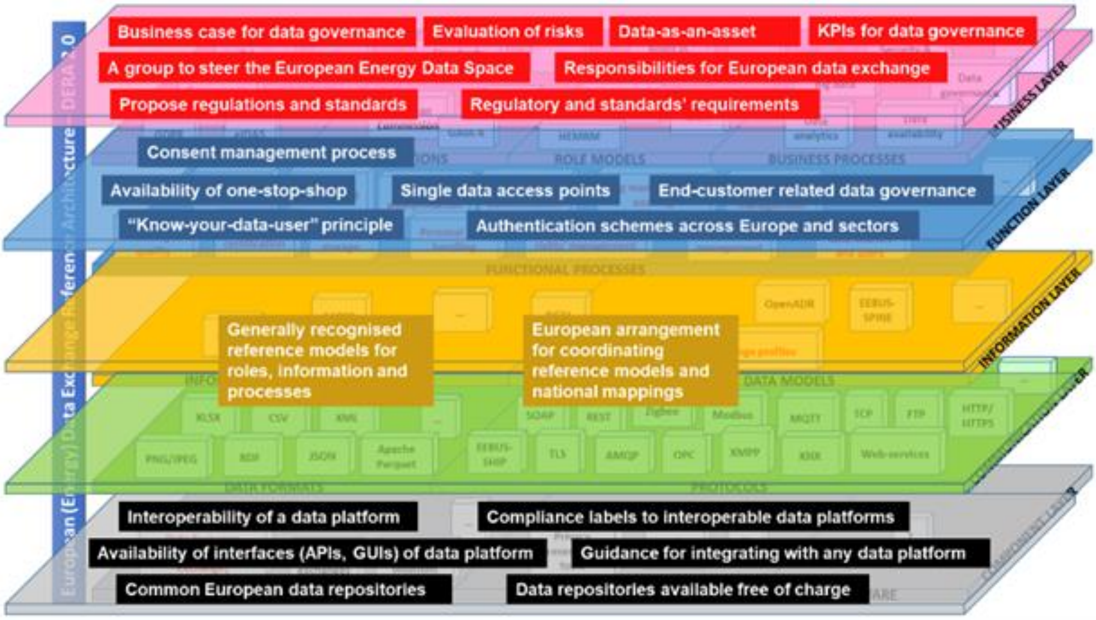

Figure 3 Elements and requirements of data governance (based on OneNet project [3],[67])

The META BUILD Data Governance Framework should be aligned with the more generic and universal Reference Data Governance Model (RDGM) that is based on the approach followed by the OneNet project [3],[67] also reflected in Figure 3. RDGM should recognise the variety of different platforms and systems, fit to different market designs and business processes, enable cross-stakeholder, cross-border and cross-sector data exchanges, ensure easy access to data satisfying GDPR requirements, facilitate TSO-DSO coordination from customer perspective, ensure scalability through open-source principle and agreed rules.

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The elements and requirements can be grouped according to the interoperability layers of Smart Grids Architecture Model (SGAM), and they complement the Data Exchange Reference Architecture (DERA) of the BRIDGE Initiative [74]. META BUILD project should attempt to make a step forward with DERA being more specific about the commonly agreed and to be taken administrative actions on European level to support the actualisation of Common Energy Data Space, and eventually the interoperability of sectoral data spaces.

Such 'administrative actions' are the building blocks of data governance and described as an example in Figure 3.

4.1.4 Core technology aspects

META BUILD will implement semantic enablers based on minimum interoperability standards, drawing inspiration from the InterConnect SIF [68]. This framework will utilise the SAREF ontology [9] as a foundation for achieving semantic interoperability across various energy domains. The key components include:

- Service Adapters: Generic Adapters (GA) with unified semantically interoperable interfaces and Service Specific Adapters (SSA) for mapping existing communication interfaces onto the SAREF ontology.
- Distributed Semantic Interoperability Layer: Known as the Knowledge Engine (KE), this layer handles knowledge exchange and querying between adapters.
- Semantic Reasoning: Utilizing ontology-based data integration to enable complex queries and inferences across heterogeneous data sources.

The methodology follows these steps:

META BUILD will implement a unified semantic layer built on SAREF4ENER [69] and IEC 61850 [70] standards. These models define a common language for energy data exchange between devices and platforms [10]. Additionally, META BUILD will explore the use of ISO/IEC 20922 (MQ Telemetry Transport - MQTT protocol) [71] to facilitate lightweight and scalable message communication in distributed energy environments.

Graph-based ontologies, such as the Common Information Model (CIM) [11], enable semantic reasoning and inference for improved data-driven decision-making and they are widely utilised by DSOs and TSOs in the industry. This allows for the identification of latent correlations between energy consumption patterns, weather conditions, and user behaviours.

The middleware solution will be based on a Service-Oriented Architecture (SOA) that enables plug-and-play integration of diverse energy services. For enabling such a solution, the FIWARE Next Generation Service Interface with Linked Data (NGSI-LD) APIs [12] can be used in order to facilitate real-time data exchange and interoperability across various energy platforms, due to their support of a rich information model and API for publishing, querying and subscribing to context information. The SOA approach also supports microservices architecture, allowing for modular scalability of energy management applications.

META BUILD will develop APIs to enable secure, standardised interactions between energy management systems, digital twins, and grid flexibility platforms (e.g. REST-oriented as well as using GraphQL [72]). These APIs will enforce OAuth 2.0-based authentication for secure access control [13]. The API layer will also support edge computing paradigms, reducing dependency on centralised cloud infrastructure.

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4.1.5 Technology progress and status

The development of semantic interoperability for energy management and flexibility planning is progressing through several structured phases. Currently, significant efforts are being made in:

- Reviewing Existing Semantic Models and Interoperability Standards: The team is conducting an extensive review of state-of-the-art semantic models, including SAREF4ENER, IEC 61850, and the CIM, to determine their applicability in energy data spaces. These models are being evaluated for their effectiveness in harmonizing data exchanges between energy assets and management systems, ensuring compliance with BRIDGE Data Exchange Reference Architecture (DERA) architecture.
- Studying Preliminary Versions of the Energy-Related Data Exchange Structure: A detailed analysis is being performed on how structured energy data is currently exchanged across platforms. This includes exploring event-driven architectures message queuing protocols (such as MQTT and Kafka), and their role in real-time energy data exchange between distributed resources, digital twins, and energy markets.
- Considering API Development for Integration: Work is ongoing in defining API endpoints, ensuring that energy assets such as heat pumps, batteries, and PV panels can communicate seamlessly with building management systems, grid operators, and demand response platforms. The goal is to develop standardised API definitions for scalable cross-platform data integration.
- Studying Security and Privacy Framework Definition: Security and privacy are paramount in energy data transactions. Investigations are being conducted into privacy-preserving federated learning, role-based access control, and attribute-based encryption to ensure GDPR-compliant data handling. These measures will support secure multi-stakeholder data exchanges, balancing operational transparency with user privacy and regulatory compliance.

4.1.6 Ongoing work

Building upon the current progress, the ongoing work that will lead to the next phases of development are:

1) In terms of refinement and expansion to support additional data types, the framework will be expanded to incorporate real-time pricing models, weather forecasts, and occupancy-based energy demand predictions. This will enhance the accuracy of demand-side response strategies and renewable energy forecasting.
2) Finalisation of Standardised APIs and Middleware for Cross-Platform Data Exchange: The final API set will include common ontology mappings, enabling seamless communication between heterogeneous energy platforms. Middleware components will be optimised to ensure scalable and fault-tolerant energy data processing.
3) Designing Advanced Semantic Queries for Energy Assets: The system will integrate SPARQL-based querying mechanisms to allow complex, ontology-driven queries across diverse energy assets. This will improve data retrieval and interoperability for energy efficiency analytics and predictive maintenance.
4) Integration with Building Digital Twin and Demand Response Modules: Semantic models will be tightly integrated with Building Information Models (BIM) and Digital Twins, ensuring real-time synchronisation between physical energy assets and their virtual representations. Additionally, demand-side management (DSM) algorithms will be implemented to dynamically adjust energy consumption patterns based on grid conditions and market signals.
5) Validation through Pilots and Real-World Testing: The framework will undergo rigorous testing in real-world pilot sites, focusing on RES integration, load balancing strategies, and proactive energy

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flexibility mechanisms. These pilot studies will assess scalability, resilience, and effectiveness in improving grid stability and optimizing Decentralised energy operations.

4.1.7 Structural view and integration points

These points are the focus of further refinement during WP4 – "Open modular energy management services" analysis and development:

- Building Digital Twins [14]:
  - Development of standardised APIs for real-time and historical energy data exchange with Digital Twin architectures.
  - Implementation of semantic data connectors for ensuring interoperable and structured integration between IoT energy devices and digital twin models.
- BIMs and Energy Management Systems:
  - Establishment of common interfaces for heat pumps, battery storage, and photovoltaic-thermal panels.
  - Implementation of automated demand response mechanisms that optimise grid interaction, self-consumption, and peak shaving strategies.
- Demand Response and Grid Interaction:
  - Deployment of a data harmonisation layer to facilitate the translation of DR signals into actionable energy optimisation strategies.
  - Integration of machine-learning-driven predictive control for real-time load shifting and grid-responsive energy management.
- Security and Access Control:
  - Implementation of attribute-based policies ensuring data privacy, role-based access management, and context-aware authentication mechanisms.
  - Development of zero-trust security frameworks to mitigate risks associated with cross-platform energy data exchanges.

4.1.8 Interoperability considerations and preliminary findings

Interoperability within the META BUILD framework requires a well-structured approach to data models, standardised APIs, event-driven architectures, and regulatory compliance. The adoption of FIWARE NGSI-LD is a key enabler for ensuring consistent energy metadata structuring and exchange across various platforms, allowing seamless integration between heterogeneous energy management systems and distributed IoT networks. This facilitates enhanced data interoperability, semantic consistency, and cross-domain collaboration, ensuring that diverse energy assets can interact efficiently within a unified ecosystem.

To enable smooth cross-platform integration, standardised API definitions are being developed to ensure compatibility with emerging energy data spaces and IoT-driven smart energy management systems. These APIs are designed to support multi-stakeholder data exchange, enhancing the interoperability of heat pumps, battery storage systems, photovoltaic-thermal units, and demand response platforms. This standardisation also allows for scalable and plug-and-play integration, reducing implementation complexity while promoting an open and extensible energy management ecosystem.

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A robust event-driven architecture is being leveraged to enable asynchronous real-time messaging, facilitating efficient communication between distributed energy assets, digital twins, and grid operators. By utilizing message queuing protocols, energy management applications can dynamically react to market fluctuations, energy demand shifts, and real-time grid conditions. This enhances the responsiveness of demand response mechanisms, optimises load balancing strategies, and improves renewable energy integration within smart grid infrastructures. Furthermore, ensuring privacy and regulatory compliance is a critical component of interoperability. META BUILD will be implementing stringent GDPR-compliant security measures, including end-to-end encryption, advanced data anonymisation techniques, and secure multi-party computation frameworks. These measures will provide a privacy-preserving infrastructure that safeguards sensitive energy data while allowing for collaborative data analytics and optimisation.

4.2 Building model for planning and MPC

4.2.1 Overview

This section explains the work done so far on the front runners that have been modelled in the course of the project to date. The focus here was on the best possible implementation of a generic modelling approach in which the building does not exactly reflect the individual properties but does contain rough characteristics. In order to pursue this approach, a few parameters are necessary, on the basis of which an adequate building twin is created. Mandatory parameters are limited to the external dimensions of the cubature, main use of the building, location, proportion of window area and age of the building and shape. With this limited selection of parameters, it is possible to create an executable simulation model in just a few steps with the help of the open-source building simulation software SimVicus [54]. TUD is the main processor of the task and works closely with the other partners to obtain the necessary information.

4.2.2 Starting status, description and constraints

The topic of generic building simulation has been an integral part of the Institute of Building Climatology for several years. The aim is to create ready-to-simulate building models that can serve as a reference for existing buildings or support architects in the development of new designs. Building Performance Simulation (BPS) can already be used in the early planning phases, in which energy and comfort factors are examined. Another step that is becoming increasingly important is the holistic consideration of the energy and environmental influences required on and in the building (Lifecycle Assessment and Lifecycle Costs).

Until now, however, model creation and data collection have been a time-consuming process for many specialist planners, which is not sufficiently remunerated, especially in the early phases. Generic buildings are an effective means of obtaining adequate information about the behaviour of the building and environmental influences.

Decisive influences are the data quality of the input parameters, as well as intensive investigations for suitable models when parameterizing the simulation models. In detail, this includes the following focal points:

- Finding matches for data with low information depth, up to detailed parameters for parameterizing complex simulation models,
- The import of existing databases and linking of components in different planning phases,
- Further development of KPIs for decision-making in the design process.

Again, detailed input parameters mean a more accurate simulation and more realistic results. Nevertheless, generic building models are an excellent approach for meaningful evaluations of effects.

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The core of the module for the use of generic buildings in SimVicus are extensive collections of floor plans based on standard buildings in Germany. The different usage zones vary depending on the cubature and use of the building. So far, the focus has been on residential and office buildings, as these make up the majority of the buildings. Further types of use will be developed and incorporated at the Institute of Building Climatology as the project progresses.

4.2.3 Core technology aspects

A core aspect of SimVicus is the linking of data from different sources. This makes it possible to obtain and import the necessary information for parameterizing a building model, for evaluating the thermal properties, energy requirements and holistic analysis of the environmental impact of the materials and energy sources used, from different sources.

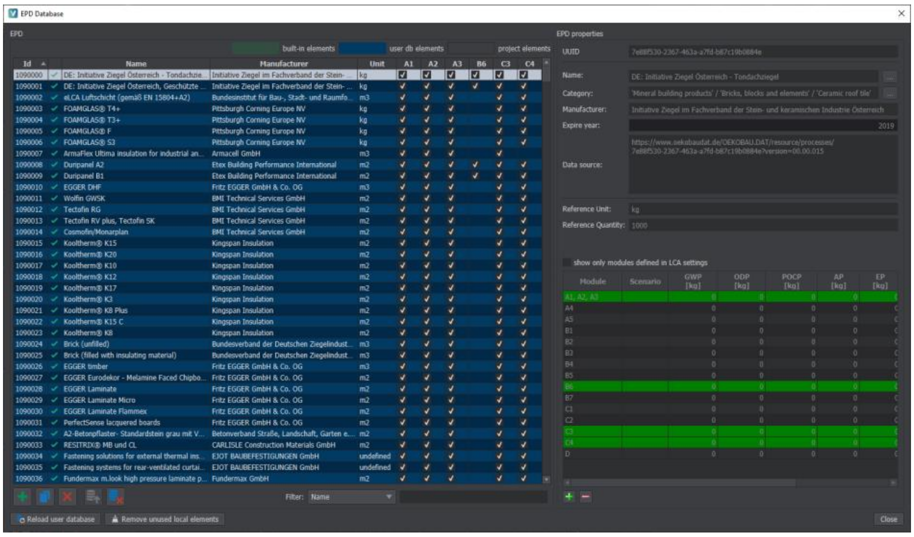

Figure 4 Database LCA for Materials

Ökobaudat [62] is a German database for environmental product declarations (EPDs) and life cycle assessment (LCA) data in construction. Managed by the German government, it provides standardised, free-to-use data for sustainable building assessments. Architects, engineers, and policymakers use Ökobaudat to evaluate the environmental impact of materials and buildings. It supports certifications like DGNB and complies with European sustainability standards. The database promotes eco-friendly construction by enabling lifecycle-based carbon footprint calculations, fostering resource efficiency, and encouraging green building practices. Regularly updated, Ökobaudat ensures transparency and reliability in sustainable construction planning.

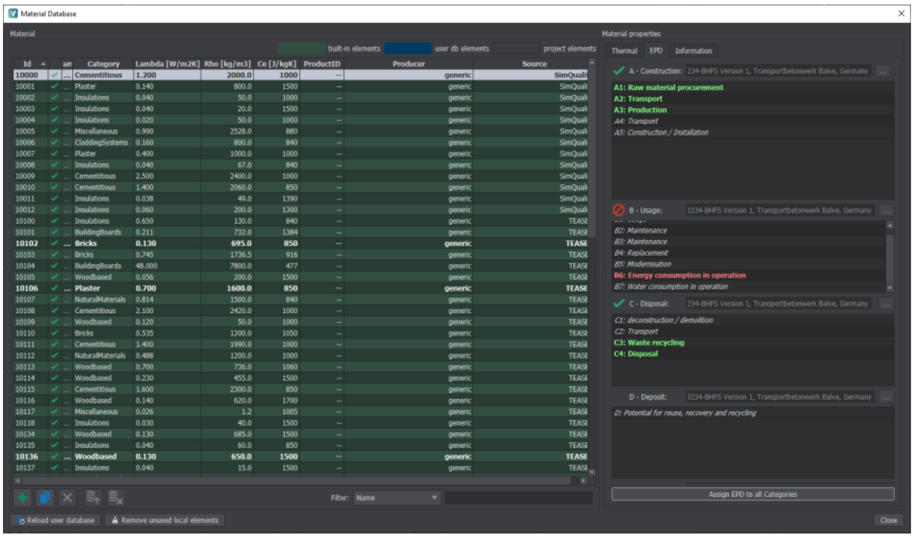

Figure 5 Material enriched with LCA Data from German Ökobaudat

Linked Data in BIM enhances data interoperability by connecting building information across platforms using several web standards. It enables seamless data exchange, improving collaboration, accuracy, and decision-making in construction projects. SimVicus also uses this concept for the parametrisation of the building models, as the extensive analyses and simulations also require different data categories. As no database provides all the information, data is imported from different databases or can be added manually. For the lifecycle assessment of a building, however, EPDs as well as thermal parameters of the materials are necessary, as the energy requirements of the building are necessary for area B: Usage.

4.2.4 Technology progress and status

The current processing status of the building models is at an advanced stage. All front runners have been parametrised and are in the process of validating the simulation results.

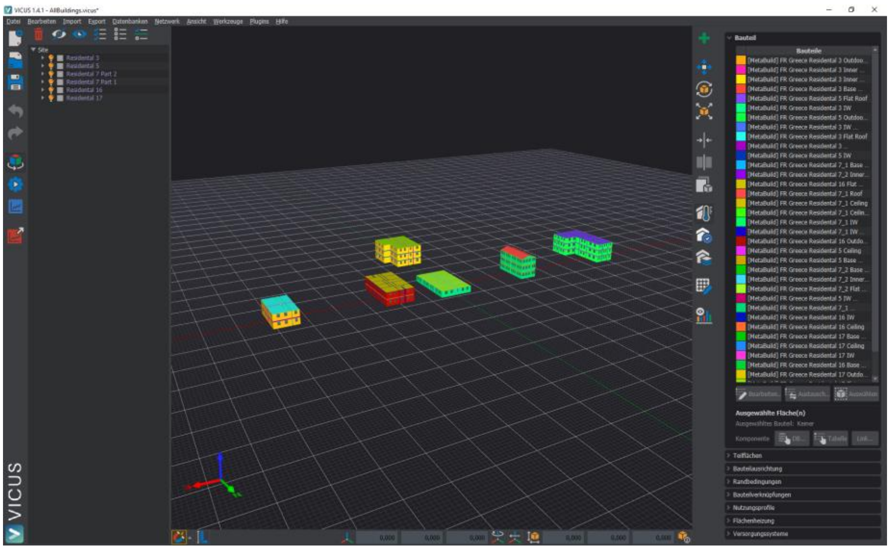

Figure 6 Generic Buildings Greek Front Runners

The best possible generic approach was also used for parametrisation, whereby usage, constructions, etc. were largely taken from databases. In a few exceptions, building-specific adaptations were made.

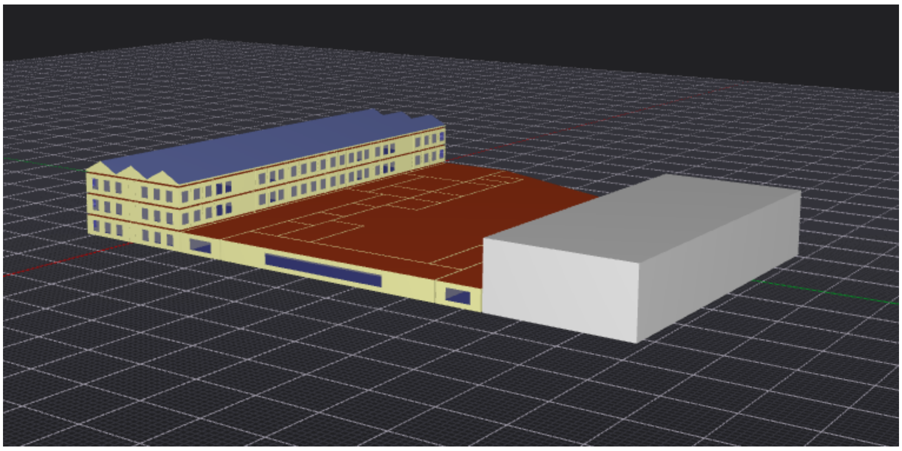

Figure 7 Detailed View French Front Runner

The objectives of the generic building approach to be investigated in the project are:

- Comparison of real measurement data and simulation
- Description of the effort required to create a generic digital twin,
- Consideration of the holistic environmental impact of buildings.

The results of the investigations will be forwarded by the Institute of Building Climatology to the partners in the work package, which will initiate further specialist investigations.

4.2.5 Ongoing work

The integration of further database interfaces for evaluating the LCA plays a decisive role in sustainable construction planning. In order to enable a comprehensive environmental assessment of construction projects, it is necessary to link various data sources with each other. By connecting database systems such as Ökobaudat, Ecoinvent [63] or GaBi [64], architects, engineers and planners can access extensive environmental data. These interfaces enable automated data integration, which improves the accuracy and efficiency of LCA calculations.

Furthermore, an innovative database with simulation models is planned, which will provide a valuable basis for the planning of sustainable buildings. The database contains a large number of representative building models. The models are easily configurable and can be customised to efficiently simulate specific designs.

Parameterizable elements such as building materials, building geometry and technical systems allow users to run through various scenarios. This enables a realistic analysis of energy performance, resource consumption and environmental impact.

Such a database supports architects, engineers and building owners in making well-founded decisions based on data and simulations. By integrating open standards and interfaces to LCA databases such as Ökobaudat, sustainable design strategies can be efficiently optimised. This contributes to the development of environmentally friendly and energy-efficient buildings.

4.2.6 Structural view and integration points

These following points are to be refined as part of the subsequent analysis and development of WP4 – "Open modular energy management services":

- Simplify data integration of historic buildings to extend generic building models,

- Import options for LCA components and data,
- Simplified data transfer of simulation results in a standardised data format.

4.2.7 Interoperability considerations and preliminary findings

Despite intensive efforts and careful development, interoperability is still of central importance, with the focus on the following points:

- International norms and standards for thermal building simulation must be more closely integrated in order to take better account of local boundary conditions. The use of the building in particular, as well as constructions, can have international deviations.
- Other KPIs for evaluating the LCA that include the transportation of materials in particular, as this can have a huge impact on the overall balance. However, data procurement is difficult and national German certificates usually ignore this aspect.
- Connecting international data sources can partially alleviate the aforementioned focus and improve the LCA for international projects.
- Increase acceptance of the BPS and simplify parametrisation, as specialist planners and intensive exchange processes are still required.

4.3 Enhancing Comfort, Energy & Performance

4.3.1 Overview

This section presents the solutions developed by INETUM, on the one hand, and the joint work of HOL and ICCS on the other hand. The former is an integrated framework for enhancing the overall performance of building energy systems through sensor driven monitoring and optimisation techniques. The latter refers to an advanced integrated platform developed by HOL and ICCS, designed to enhance user comfort, energy efficiency, and overall building performance. By leveraging AI models, real-time monitoring, and IoT-enabled automation, the platform intelligently optimises energy consumption and building operations. Both systems aim at addressing critical challenges identified in BEMs through predictive analytics and user feedback integration, while promoting sustainable energy consumption and minimizing costs.

4.3.2 Starting status, description and constraints

The platform is currently deployed in pilot buildings equipped with essential smart components, including smart meters, smart plugs, environmental sensors (IAQs), and heat pump controllers.

Initial constraints and challenges include:

- Data Integration Complexity: Fragmented data streams from various smart devices require seamless aggregation and interoperability.
- Predictive Capabilities: Enhancing the accuracy of forecasting energy demand, comfort needs, and market price fluctuations remain an ongoing challenge.
- User Interaction: Ensuring an intuitive user experience while balancing energy-saving strategies with individual comfort preferences.

Regulatory Compliance: Adhering to strict data privacy regulations such as GDPR and ensuring secure data transmission and storage.

The current framework is built on existing residential and commercial building setups equipped with foundational energy systems such as HVAC, lighting, and environmental sensors. Some initial challenges identified thought a preliminary literature review include:

- Heterogeneity of Systems and Data: Existing buildings often use disparate systems, leading to fragmented data streams and integration difficulties.
- Limited Predictive and Adaptive Capabilities: Many systems lack the ability to anticipate changes in environmental conditions or user behaviour.
- User-Centric Challenges: Balancing energy efficiency with user-defined comfort preferences remains a significant constraint.
- Regulatory Compliance: Adhering to data privacy laws (e.g., GDPR) and energy regulations adds complexity.

4.3.3 Core technology aspects

The following part depicts the technology aspects of the Home Management System that is being built within the scope of META BUILD. The architectural view of this system is depicted in Figure 8.

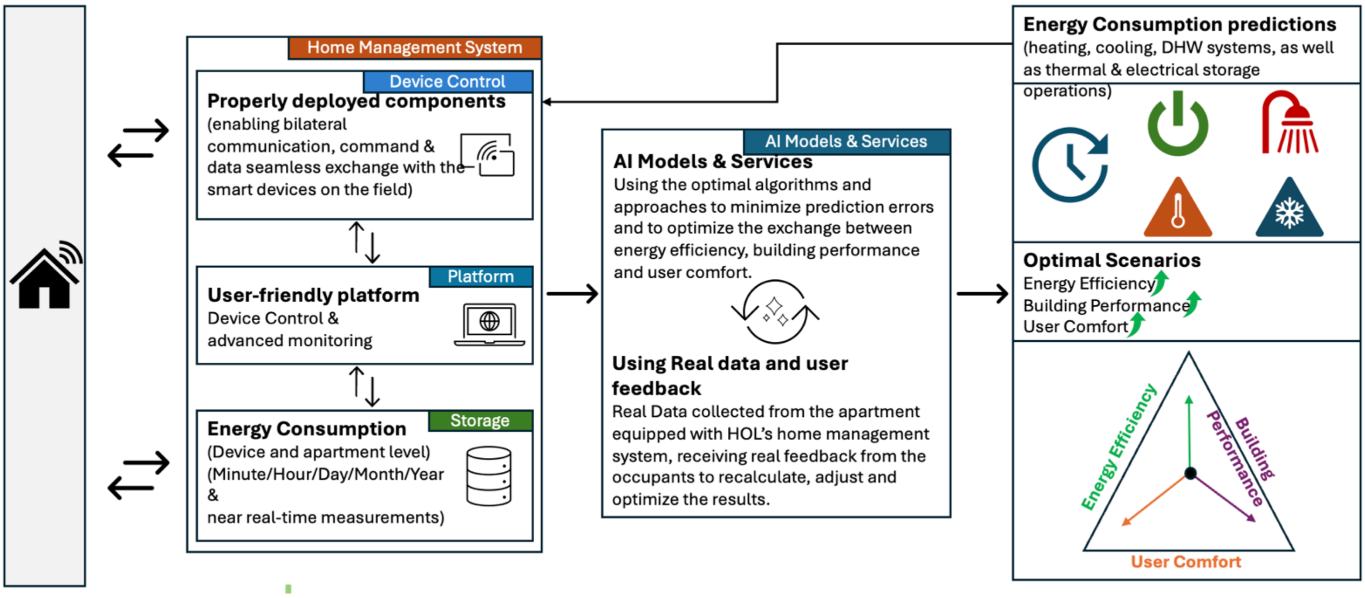

Figure 8 Integrated Platform Architecture

Key technological components of the platform include:

- Advanced Monitoring: Real-time energy consumption and environmental data collection at device (e.g., smart plugs, heat pumps) and apartment levels, with granular insights (minute/hour/day/month/year).
- AI Models and Services: Precise forecasting of energy demand (heating, cooling, DHW systems, thermal and electrical storage operations) and optimisation based on predictive algorithms.
- Device Control: Bilateral communication with smart devices in the field, enabling remote command and seamless data exchange.
- User-friendly Platform: Mobile apps for users, web apps for users and aggregators, providing real-time insights and control capabilities.

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Storage Solutions: Hybrid edge and cloud storage mechanisms for real-time and historical monitoring of energy consumption and production data.

The framework relies on key technological components to overcome BEMS challenges:

- Intelligent Comfort Monitoring Systems: Deployment of IoT sensors to collect real-time data on environmental conditions (e.g., temperature, humidity, air quality) and energy usage.
- Predictive Analytics for Comfort and Energy: Advanced models for forecasting energy demand and optimizing comfort settings based on user behaviour and environmental trends.
- Adaptive Control Mechanisms: AI-driven algorithms that dynamically adjust HVAC and lighting systems to balance comfort and energy efficiency.
- Integration with Market Signals: Linking the system with energy market data to align energy usage patterns with dynamic pricing or renewable energy availability.

4.3.4 Technology progress and status

The platform is currently in a pilot phase, with notable progress:

- Deployment of IoT devices including main energy meters, environmental sensors – IAQs and smart plugs, enabling real-time data collection and advanced monitoring.
- Development of a REST API for monitoring and controlling heat pumps remotely through the cloud.
- REST API implementation for environmental data collection from IAQs.
- Development and testing of AI-driven forecasting models and optimisation algorithms to minimise prediction errors and balance energy efficiency, building performance, and user comfort.

Successful integration of real data and user feedback from apartments equipped with the HOL home management system.

The framework is in the initial stages of development, with key progress made in:

- Implementing IoT-based environmental monitoring in pilot buildings.
- Developing predictive models for energy demand and comfort parameters.
- Testing adaptive control strategies to enhance system responsiveness to real-time data.
- Assessing interoperability challenges across various sensor platforms and energy systems.
- Further efforts are focused on refining the scalability and adaptability of these solutions, as highlighted by recent findings in the literature.

4.3.5 Related studies and ongoing work

For the further development of the services a study was conducted to achieve Building Performance Optimization (BPO). This technique addresses a multi-objective problem where a building's emissions reduction constitutes a co-optimization goal. Luo et al. (2024) [55], in an extensive review of data-driven retrofit optimization studies, present a distribution heatmap of carbon emissions reduction co-occurrence with other research goals. They report that reducing carbon emissions is typically coupled with reducing energy consumption, retrofit and operational costs, and improving indoor thermal comfort. In a bi-objective approach, Panagiotidou et al. (2021) [56] employed a Multi-Objective Genetic Algorithm (MOGA) to minimize annual GHG emissions and the life cycle cost of a multi-residential building in different Greek climate conditions. Dou et al. (2023) [57] established a mathematical optimization model for decarbonization-based retrofit of existing office parks, considering the relationship between cost, energy consumption, and carbon emissions, aiming for maximum carbon emissions reduction throughout the park's entire life. Rosso et al. (2020) [58]

searched for optimal retrofit solutions to minimize annual CO_2 emissions, annual energy consumption, investment and annual energy costs for a building in Mediterranean climate conditions through an aNSGA-II optimization algorithm.

Despite the annual analysis conducted in [58], most studies prefer to evaluate a building's performance over its lifetime (life-cycle), as it provides a holistic view of its environmental impact and examines long-term sustainability rather than short-term performance. Shardam and Mukkavaara [59] explored the impact of various passive energy efficient measures on life-cycle sustainability (life-cycle costs, life-cycle energy consumption and life-cycle carbon impact minimization), when accounting for the profitability of the building's floor area. Similarly, Luo and Oyedele [60] proposed a novel data-driven life-cycle optimization approach to examine optimal life-time cost, energy consumption and carbon emissions minimization scenarios based on passive measures. Passive measures typically involve modifications on the building's envelope (e.g., adding wall insulation, replacing single-glazed windows, etc.) which is one of the main elements considered in relevant studies.

Based on the state-of-the-art, the next steps of this work at technology level include:

- Enhancing forecasting models by integrating deeper historical data, advanced machine learning techniques, and increased user feedback.
- Refining protocols for seamless communication among IoT devices, energy systems, and external market signals.
- Expanding user studies to optimise adaptive control mechanisms further and ensure user comfort and active engagement.
- Expanding the depth and accuracy of forecasting models by integrating historical data, machine learning algorithms, and user feedback.
- Developing standardised protocols to enable seamless communication between IoT devices, energy systems, and external market signals.
- Conducting user studies to fine-tune the system's adaptive control mechanisms while ensuring comfort and engagement.
- Extending pilot deployments to a broader range of buildings and contexts, evaluating the framework's adaptability to different environments.

4.3.6 Structural view and integration points

The platform emphasises modularity and scalability, comprising:

- Centralised Platform: A unified interface integrating advanced monitoring of real-time data streams, AI-driven analytics, and device control for dynamic, real-time decision-making.
- Data Integration Layer: Middleware enabling seamless aggregation of data from diverse IoT devices, energy management systems, and market APIs.
- User and Administrator Interfaces: Mobile and web applications offering intuitive dashboards for real-time monitoring, control, and insights tailored to different stakeholders.

The framework's architecture emphasises modularity and scalability, with the following core components:

- Centralised Monitoring and Control: A unified platform integrating sensor data, predictive models, and control algorithms for real-time decision-making.

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- Data Integration Layer: Interoperable modules that aggregate data from diverse sources (e.g., HVAC, lighting, market APIs).
- User and Administrator Interfaces: Dashboards offering real-time insights on energy usage, comfort levels, and system performance, tailored to different stakeholder needs.

4.3.7 Interoperability considerations and preliminary findings

Interoperability considerations and preliminary findings Interoperability remains essential, with key considerations being:

- Adoption of common data schemas for seamless integration across devices and systems.
- Strong emphasis on data privacy, encryption, anonymisation, and informed consent.
- The scalability of the solution to maintain functionality and efficiency as the number and diversity of integrated devices grow.

Interoperability remains a critical challenge for BEMS, as noted in ongoing literature reviews. Key considerations include:

- Developing and adopting common data schemas for seamless integration across devices and platforms.
- Ensuring data privacy and compliance through encryption, anonymisation, and informed consent mechanisms.
- Designing solutions that remain functional and efficient as the number of integrated devices and data sources grows.

4.4 MPC control of MFH energy system

4.4.1 Overview

This section presents the concept and development roadmap of the Model Predictive Control (MPC) system for Multi-Family Housing (MFH) energy systems. The goal of this technology is to optimise the energy-related costs and efficiency of heat pump operations by leveraging predictive control strategies. The approach builds upon iDM's existing iON energy optimiser, originally developed for Single-Family Housing (SFH), and extends its capabilities to MFH applications.

The aim of our technology is to develop MPC for MFH energy systems to efficiently operate the HPs combined with thermal energy storage. The goal is to implement the models and control algorithm on an edge device, which will be deployed at the pilot site. Below, we provide an overview of various components (models and algorithms) of the technology.

Reduced order heat pump model

EURAC Research developed a reduced-order model for simulating various heat pumps. This grey box model uses performance maps for thermal power and electrical consumption calculations based on four key variables: inlet temperatures, compressor speed, and mass flow rates. The model operates as a state machine, modulating compressor speed based on the inlet temperature and setpoint. Two modulation algorithms are available. The fixed ramp algorithm in which the compressor speed changes in predefined increments, with transitions based on specific signals and timers. The PI control algorithm adjusts speed

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based on the difference between inlet temperature and setpoint once certain conditions are met. Training the model is essential for accurate results; otherwise, it scales default performance maps.

The innovative aspect of the heat pump model is its automatic training algorithm, which minimises model mismatch and allows adaptation to any existing heat pump. This algorithm significantly improves the accuracy of the model. The training process can utilise monitoring data, laboratory tests, or information from the heat pump manufacturer. It effectively adjusts the model to align with real operational behaviour, including during transitional phases.

The reduced order model of the heat pump has been validated using both monitoring and laboratory test data, demonstrating the robustness of its automated training algorithm for correlating thermal power and electrical consumption with operating conditions. However, the model struggles with accurately identifying the correct modulation of the heat pump. The fixed ramps algorithm simplifies real control mechanisms, yielding satisfactory results for energy analysis but falling short in control optimisation accuracy. In contrast, the PI control algorithm offers improved accuracy but requires user intervention to fine-tune its parameters for optimal performance.

Additionally, an automated algorithm for identifying PI control parameters is under development but is not yet implemented in the model. In the future, this algorithm will be further developed and included in the model.

Thermal energy storage model

EURAC Research developed a novel ROM designed to simulate thermal stratification in TES systems, with a particular focus on thermocline dynamics for real-time control applications. The model simplifies the sophisticated dynamics of TES by dividing the tank into discrete zones and dynamically modelling thermocline movement based on varying inflow conditions. By accurately replicating thermal behaviour while maintaining computational efficiency, the model adheres to fundamental physical principles to ensure the conservation of mass and energy, thereby supporting efficient energy management in TES applications. The model has been experimentally validated in laboratory conditions, demonstrating its practical applicability and reliability for real-world scenarios.

Building's thermal load model

EURAC Research developed a reduced order model, using an Artificial Neural Network (ANN) model for simulating the building's thermal load due to space heating. The innovation of the model developed is mainly related to the level of detail considered. In fact, it accounts for the presence of a heating system controlled by local thermostats, and the sampling time considered is well below 1 hour. In the literature, different examples of using ANN models for predicting the space heating load of a building are available. Nevertheless, they generally focus on longer sampling times (from 1 hour) and do not account for the typical ON-OFF operations of heating systems controlled by dwellings or zone thermostats.

Future investigations should focus on different aspects. The first is related to the improvement of the performance in terms of the accuracy of the predictions and replicability of the results. The second is related to the inclusion of the indoor temperature set point in the model. The third is related to the development of a model that can ensure similar performance in terms of accuracy in the space heating thermal load prediction, with lower computational capacity and time.

The following subchapters provide an overview of the initial state of the technology, its core technical aspects, progress status, and planned future steps. Additionally, integration and interoperability considerations within the META BUILD ecosystem are outlined.

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Multi-dimensional dynamic programming

EURAC has taken the standard implementation of the dynamic programming (DP) for a receding horizon MPD and refined it. It now yields better-quality solutions with less computational runtime. This approach is tried and tested for the one-dimensional case, i.e., with one control variable. The current work is focusing on expanding the approach to a n-dimensional setting, as well as exploring hybrid solutions, where the DP finds a suitable solution candidate on a coarse DP grid, and a heuristic or metaheuristic approach further refines it.

4.4.2 Starting status, description and constraints

After several years of development and an extended testing phase, iDM introduced its iON energy optimiser in Q1 2025. This digital product is designed for integration with iDM's heat pumps, primarily targeting single-family housing applications. The iON optimiser serves as a foundation for the upcoming MPC-based solutions that will be adapted and expanded for MFH energy systems.

The primary function of the iON energy optimiser is to minimise energy-related costs by solving an optimisation problem that accounts for:

- Dynamic electricity cost curve over the next 24 hours
- Temperature-dependent efficiency of heat pumps
- Predicted photovoltaic energy production over the next 24 hours

To achieve this, the system utilises a dynamic building model in conjunction with historical energy consumption data to forecast the thermal energy demand for space heating and domestic hot water. This holistic optimisation approach ensures efficient and cost-effective energy management while considering external and internal influencing factors.

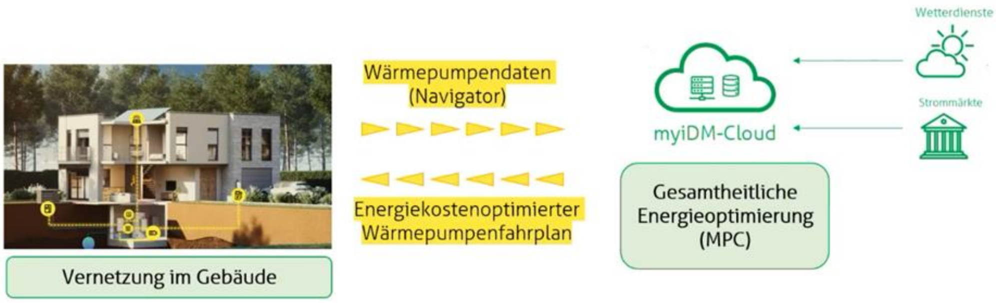

Figure 9 Structural view of iON optimiser - for SFH applications

Figure 9 provides a structural overview of the iON optimiser as applied in SFH. While effective for SFH applications, adapting this technology for MFH introduces additional complexity. The MPC system must be capable of managing multiple thermal zones with varying heating demands and operational constraints. The development of a single room heating control module, the “Zonenmodul”, is a critical step in enabling precise monitoring and control across multiple dwellings with multiple rooms. Additionally, billing mechanisms for multi-dweller configurations need to be defined in accordance with regulatory requirements.

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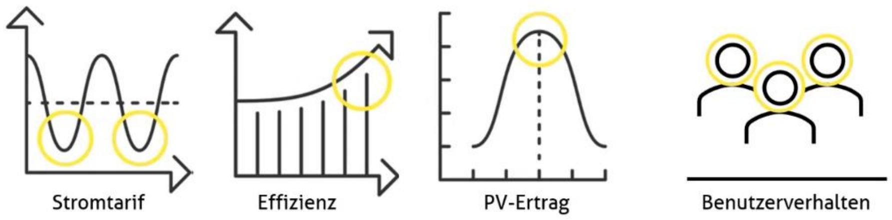

Figure 10 Holistic optimisation, considered variables: dynamic el. cost, efficiency, pv-production, occupancy behaviour

Figure 10 illustrates the holistic optimisation approach of the iON optimiser, showing the key variables considered: dynamic electricity pricing, heat pump efficiency, PV production forecasts, and occupancy behaviour. This optimisation framework must be extended for MFH applications by integrating additional sensor data and control for multiple thermal zones.

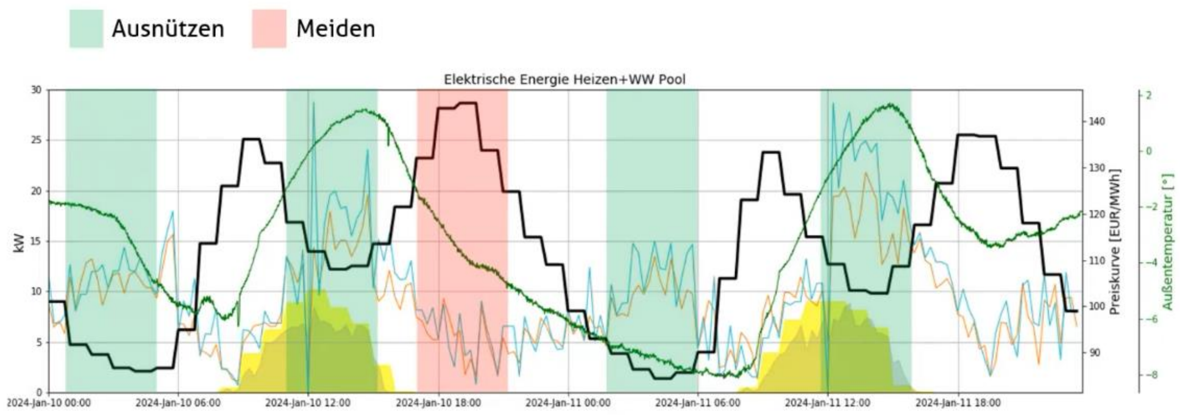

Figure 11 Two days of iON operation - Timeseries Data (legend is explained in the text)

Figure 11 presents a two-day timeseries of iON operation, showcasing both predicted (orange) and actual (blue) electric power usage across a pool of heat pumps. Input data, including the electricity cost curve (black), ambient air temperature (green), and predicted PV production (yellow), is used during optimisation. The actual PV production is indicated in gray. Green-shaded areas highlight periods of low-cost, high-efficiency operation, whereas red-shaded areas depict high-cost operation with reduced efficiency due to factors such as low PV production and increased electricity prices. Deviations between predicted and actual electricity consumption arise from unpredictable disturbances such as user behaviour (e.g., unexpected DHW tapping, extended ventilation, or auxiliary heating with wood stoves).

Reduced-order heat pump model

The heat pump model developed by Eurac Research is a reduced order model to simulate the operation of any heat pump. This reduced order model represents a single stage heat pump with a variable speed compressor and can be used to model different typologies of heat pumps (air-to-air heat pumps, air-to-water(brine) heat pumps, water(brine)-to-air heat pumps and water(brine)-to-water(brine) heat pumps). This is not a first principal model since the thermal power's and the electrical consumption's computation relies on performance maps data provided by the user, and used to train the model. Thus, it is a grey box model. The thermal power and the electrical consumption are a function of four independent variables (inlet temperatures, speed of the compressor and mass flow rate at the load side). Table 1 presents the input and outputs of the model respectively.

Table 1 Inputs and outputs of the MPC model

	INPUTS		OUTPUTS	
1	Heating signal	[-]	Speed of the compressor	[Hz]
2	Cooling signal	[-]	Thermal power	[W]
3	Inlet temperature at load side	[°C]	Electrical consumption	[W]
4	Mass flow rate at load side	[kg/s]	COP	[°C]
5	Inlet temperature at source side	[°C]	Outlet temperature at load side	[°C]
6	Mass flow rate at source side	[kg/s]	Mass flow rate at load side	[kg/s]
7	Heating set point	[°C]	Outlet temperature at source side	[°C]
8	Cooling set point	[°C]	Mass flow rate at source side	[kg/s]

Besides the inputs and outputs, the heat pump model has a set on internal parameters that allow to tune the model. The heat pump is modelled as a state machine. The state of the system is defining the speed of the compressor. The speed of the compressor is modulated according to the inlet temperature at the load side and a setpoint. The model tries to track the setpoint temperature with two different algorithms. It is up to the user to select which modulation to use.

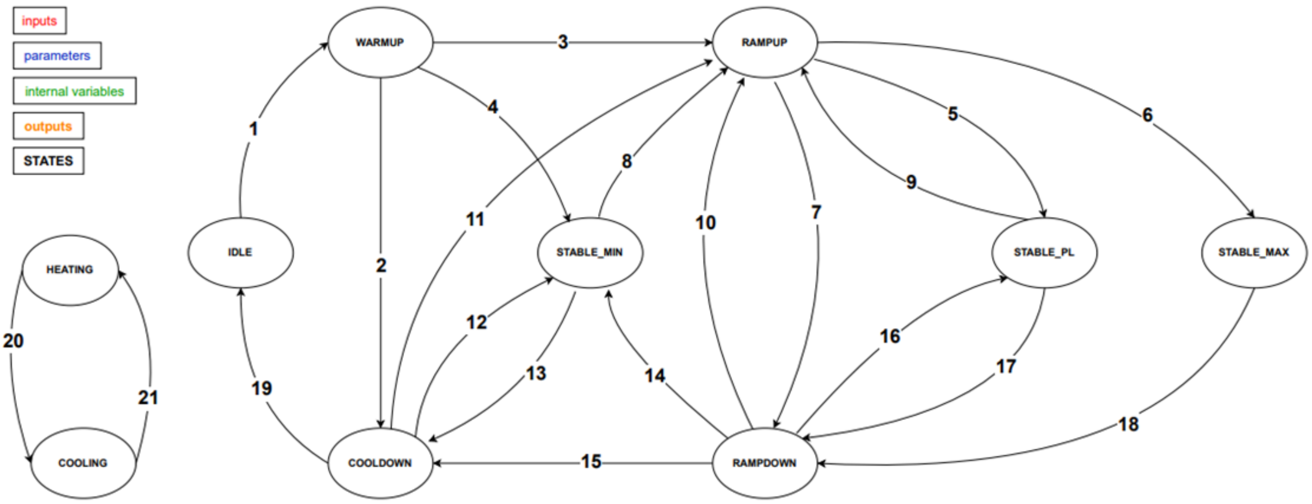

Figure 12 State machine diagram of heat pump model for modulation 1

The first algorithm is a state machine in which the speed of the compressor is modulated with fixed ramps. This means that the acceleration and the deceleration of the compressor are fixed. Figure 12 shows the diagram of the first algorithm. To move from one state to another there is a specific transition function that needs to be met. The transitions are mainly function of activation and deactivation signals, the comparison between the inlet temperature at load side and the setpoint temperature, and some internal timers.

Figure 13 shows an example of the compressor's speed modulation according to the first algorithm.

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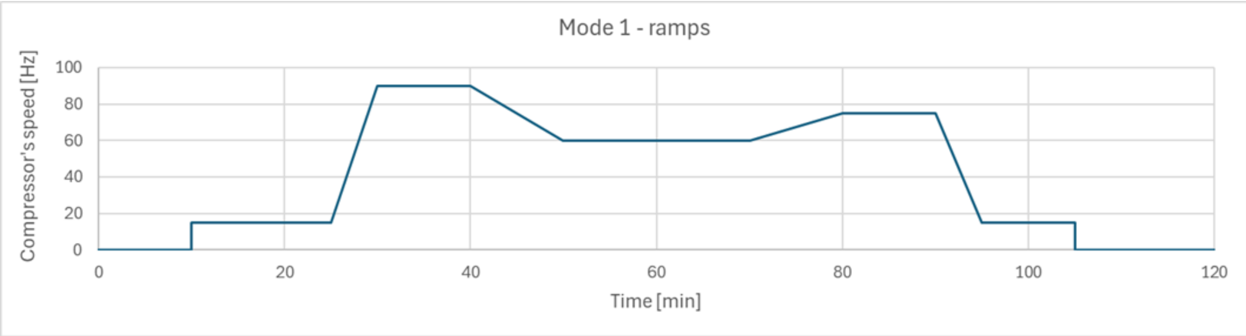

Figure 13 Example of compressor's speed variation according to modulation 1

The second modulation algorithm relies on a PI control (Figure 14). Some conditions need to be met for the model to start operating in the "PI" state. Once this state is reached, the modulation of the compressor speed only depends on the comparison between the inlet temperature at load side and the setpoint temperature.

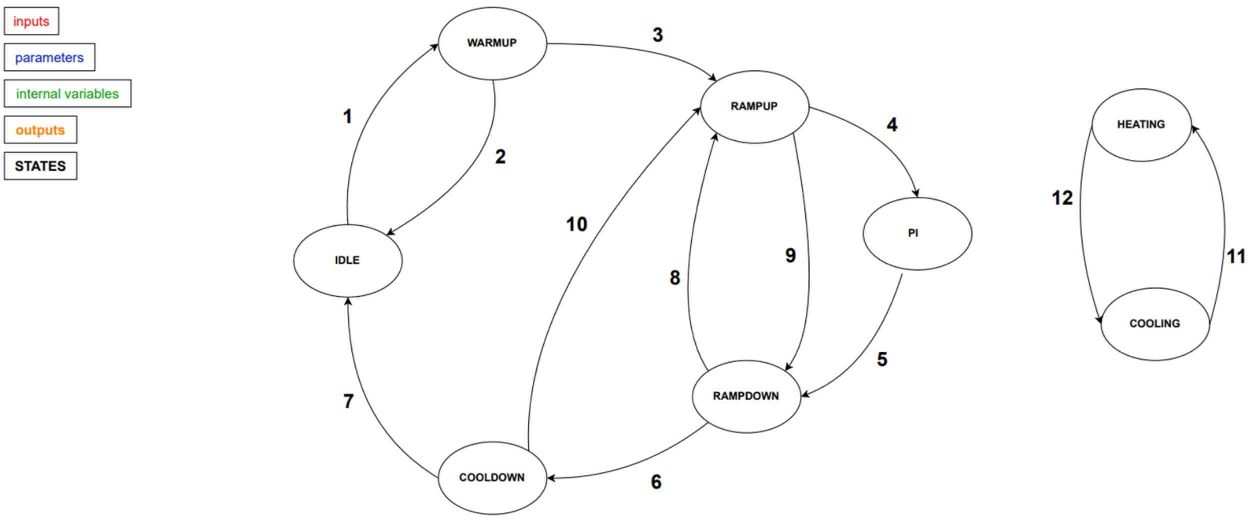

Figure 14 State machine diagram of heat pump model for modulation 2

Figure 15 shows an example of the compressor's speed modulation according to the first algorithm.

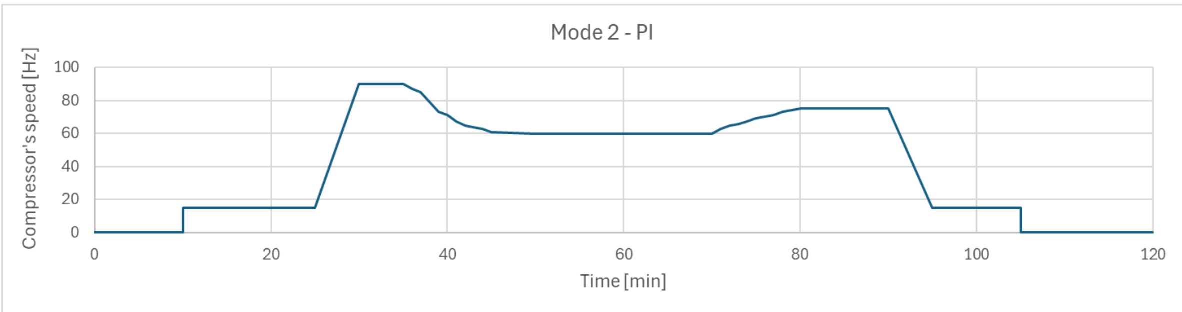

Figure 15 Example of compressor's speed variation according to modulation 2

If the heat pump model is not trained, it is not possible to obtain the correct results for the thermal power and electrical consumption. In this case, the model relies on default performance maps that are scaled according to the nominal thermal power and nominal COP of the actual heat pump.

Thermal energy storage model

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The ROM of TES is an efficient method for simulating thermal stratification and energy dynamics in hot water storage systems. The model is designed to optimise computational efficiency while maintaining accuracy, making it suitable for real-time control applications that require rapid simulations. The tank is divided into discrete zones, with the movement of thermoclines modelled based on varying inflow conditions to accurately replicate the thermal behaviour. The conservation of mass and energy is guaranteed by the implementation of the underlying physical equations. This section details these underlying physical principles, mathematical formulations, state logic, and implementation strategies of the model. Additionally, it outlines the procedures for testing and validating the model across various thermal scenarios. Figure 16 illustrates the configuration of the TES system, featuring a cylindrical tank with height H and radius r, designed to capture thermal stratification and interactions between temperature layers.

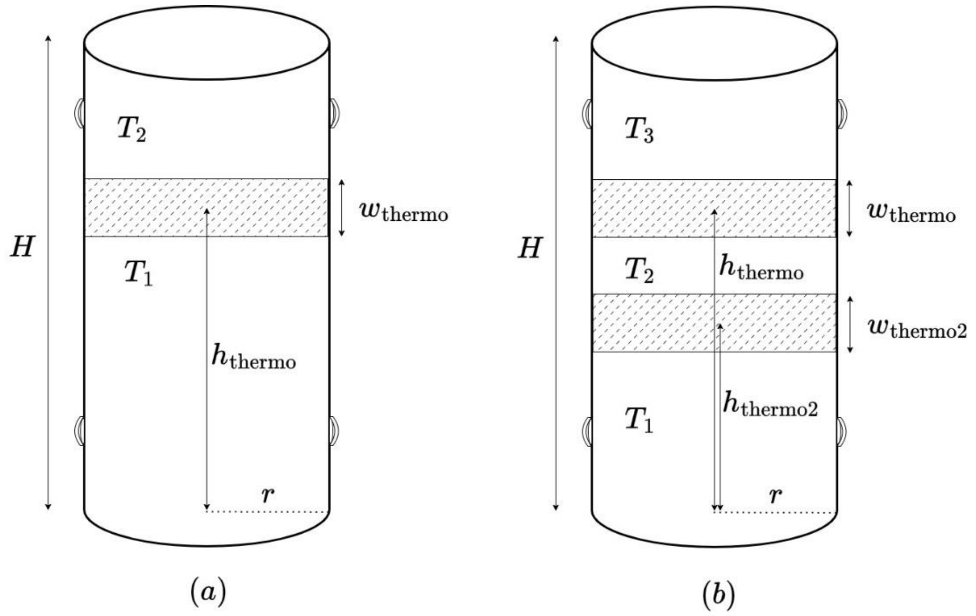

Figure 16 Schematic of TES with one (a) and two (b) thermocline layers.

In Figure 16(a), the tank is divided into two temperature segments, T_1 (lower) and T_2 (upper), separated by a thermocline of thickness W_{thermo} at height h_{thermo} from the base. The thermocline's thickness and position vary over time due to water inflow dynamics. Figure 16(b) presents a different TES state featuring two thermoclines, resulting in three temperature layers: T_1 (lower), T_2 (middle), and T_3 (upper). The presence of a second thermocline reflects conditions that can occur in practice, where inflow patterns and thermal mixing result in more complex stratification within the tank. The primary thermocline, with thickness W_{thermo}, is at height h_{thermo}, and the secondary thermocline, with thickness $W_{thermo2}$, is at height $h_{thermo2}$. Both thermoclines adjust dynamically, influencing thermal energy movement and the overall temperature distribution.

Building on this stratified configuration, the tank is modelled by partitioning it into zones corresponding to the temperature layers defined by the thermoclines. To maintain energy balance within the system, each zone is assigned a specific temperature. Depending on the thermal state of the tank, it can be divided into one, two, or three zones.

State-based modelling approach

The thermal behaviour of the TES is complex due to the formation and movement of thermoclines under varying operational conditions. To model these dynamics effectively, the tank's operation is categorised into specific states based on the number of thermoclines present, their behaviour (forming, moving, or disappearing), and the direction of the dominant flow (charging or discharging). These states, summarised in Table 2, streamlines the modelling process by enabling the use of specific equations and logic for each distinct scenario. States are structured with digits that indicate the flow direction and thermocline behaviour:

First digit: Denotes the dominant flow direction:

1. for top inflow (charging).
2. for bottom inflow (discharging).

Subsequent digit: Represents the status of the thermoclines:

1. indicates a thermocline is expanding (forming).
2. indicates a thermocline is moving (advancing through the tank).

For states with two thermoclines, the digits sequentially represent the behaviour of each thermocline from top to bottom. This structured classification, shown in Table 2, captures all possible operational scenarios, enabling smooth transitions between states based on the tank's real-time conditions.

The schematic of a case involving three thermal layers is shown below:

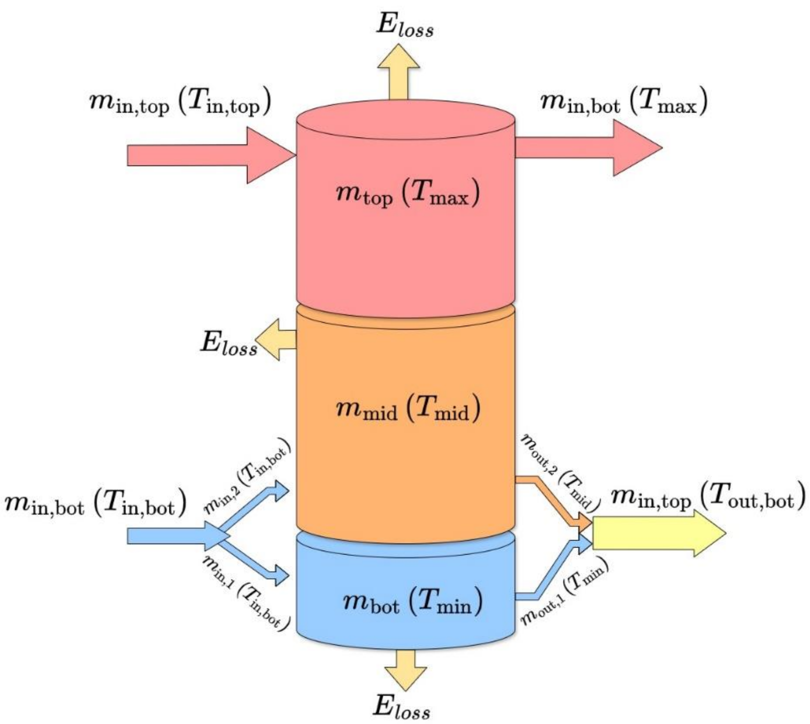

Figure 17 Schematic of case involving three thermal layers

Table 2 Classification of TES operational states based on flow direction and thermocline behaviour

Category	State	Description
General	0	Idle
	30	Non-stratified tank
Top inflow (charging)	11	Thermocline expanding
	12	Thermocline moving
	112	Two thermoclines: expansion (1st), movement (2nd)

	122	Two thermoclines: movement (1st and 2nd)
Bottom inflow (discharging)	21	Thermocline expanding
	22	Thermocline moving
	212	Two thermoclines: expansion (1st), movement (2nd)
	222	Two thermoclines: movement (1st and 2nd)

Building's thermal load model

The model developed is an ANN model. The choice of using an ANN model to calculate the building's thermal space heating load is based on different considerations (see more details in the next section).

Figure 18 shows the schematic of the ANN model, with inputs, outputs, and internal connections. The data used as input are related to external weather conditions (external temperature and global horizontal irradiation (GHI)), to heating system operation (indoor temperature of the considered zone/dwelling/building and space heating load), to the use of the building (electrical consumption due to electrical appliances) and to the time (day of the week and second of the day) to catch specific trends along some hours of the day or some days of the week.

The outputs of the model are the indoor temperature of the considered zone/dwelling/building and the space heating thermal load. As can be noted in Figure 18, the model is, in reality, composed of two sub-models, one predicting indoor temperature and one predicting space heating thermal load. Actually, we use the two sub-models connected to have only one output from each sub-model.

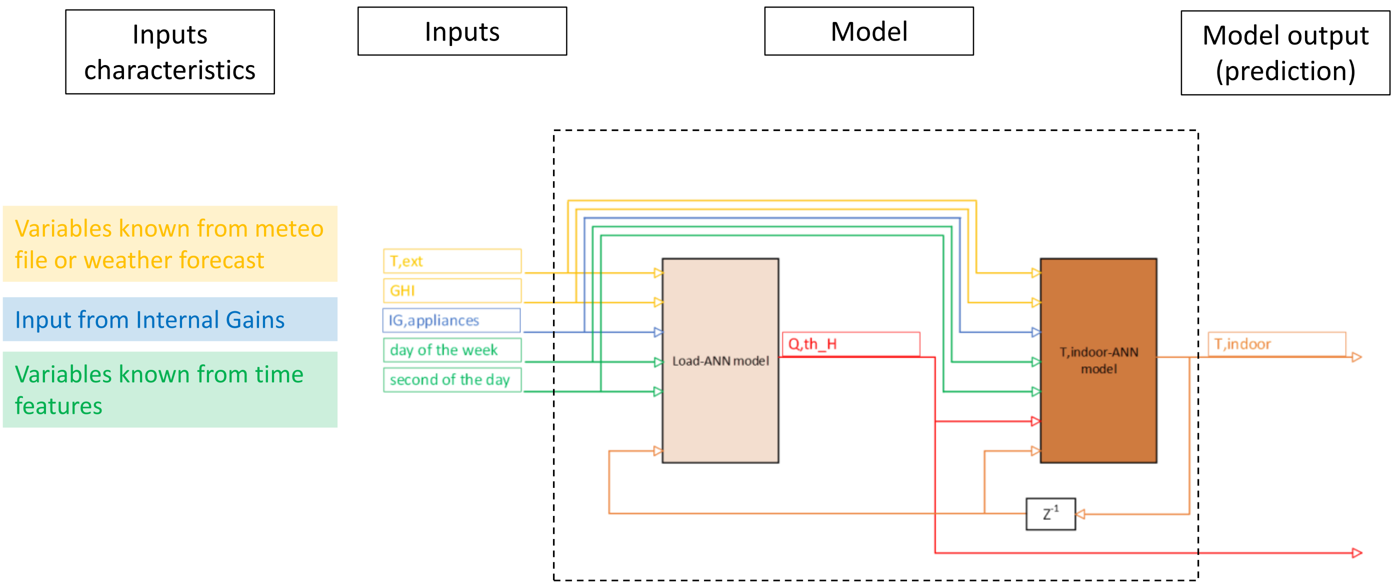

Figure 18 Schematic of the ANN model used to predict space heating thermal load and indoor temperature

The model presented in Figure 18 is trained using the input data of the last two weeks. To improve performances, the model is also re-trained every 24 hours to have an always updated training period. The model is used to predict the space heating thermal load for the next 24 hours with a sampling time of 5 minutes.

Multi-dimensional dynamic programming

DP has been used in many different fields that involve sequential decision-making. One setup that lends itself to dynamic programming particularly well is a receding horizon model predictive control. One key decision to make when using DP is how to discretise the problem. Finer discretisation steps lead to better solutions but require more runtime. More coarse discretisation steps compute much faster but yield a lower solution quality.

DP also suffers from the curse of dimensionality: Every new dimension that is added to it increases the complexity by the amount of discretisation steps of that dimension squared. So, adding a dimension with only 10 discretisation steps already increases the computational complexity by a factor of 100.

4.4.3 Core technology aspects

The MPC system for MFH is built upon several core technological components:

- Mathematical Building and System Component Models to formulate optimal control problem
  - (Multi-zone) building model.
  - Heat pump model.
  - Heat distribution model.
  - (PV-Production model).
  - Heat source model (ground, air temperature or PVT).
- Weather forecast service.
- Solver algorithm for the optimal control problem.
- Server Infrastructure (cloud-based servers for computing the optimal control strategy).
- Data management (Database with historical, real-time and forecast data).
- Monitoring / Control interfaces.
- Communication Infrastructure.

Reduced-order heat pump model

The core innovation of this model is the automatic training algorithm. This algorithm allows to reduce the model mismatch and allows to adapt the model to any existing heat pump. Figure 19 shows an example of how the training algorithm improves the model mismatch. In the figure the orange line corresponds to the monitored thermal power, the blue line is the thermal power calculated by the reduced order model, the red line is the monitored electrical consumption of the heat pump, and the green line represents the electrical consumption calculated by the model. It is possible to notice that in the upper figure, in which the model is not trained, the model mismatch is massive. The bottom figure shows the results of the model after the training algorithm is applied. The model mismatch is drastically reduced.

This training algorithm allows on one side to adapt the model to the real operation of the simulated heat pump, on the other side to account for the heat pump behaviour during transitional periods (i.e. during activations). However, it is mandatory to train the model either with monitoring data, laboratory tests data or data provided by the heat pump manufacturer.

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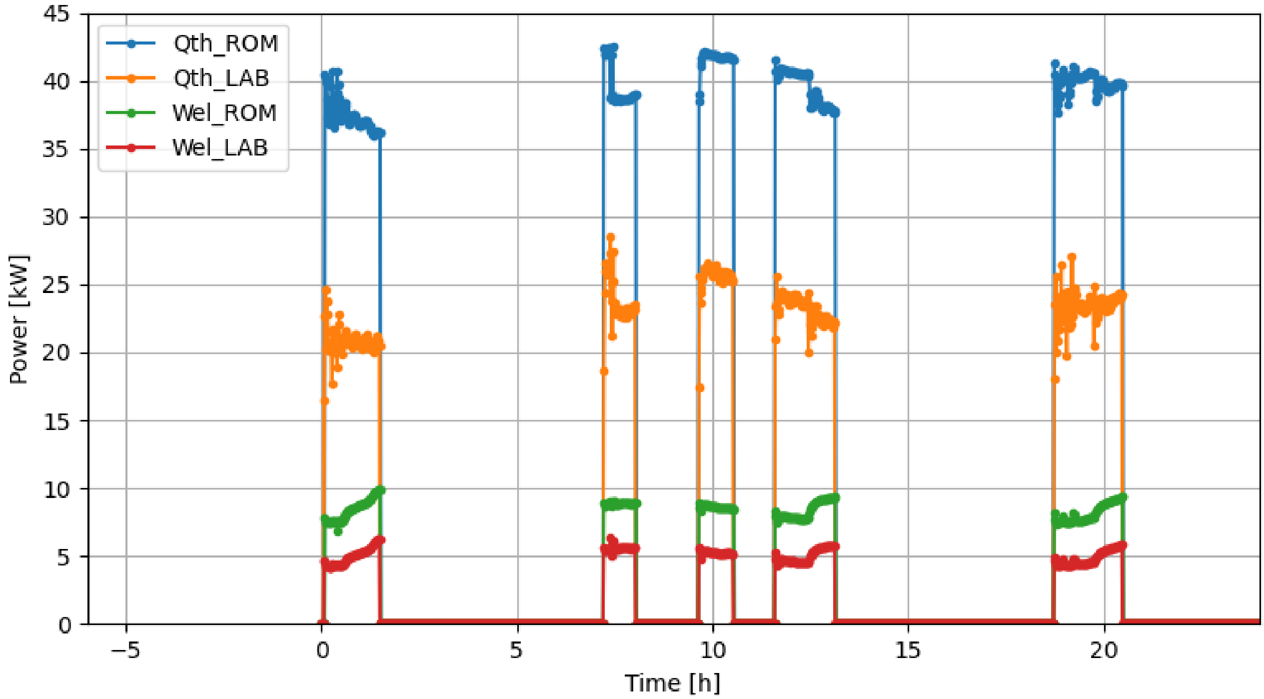

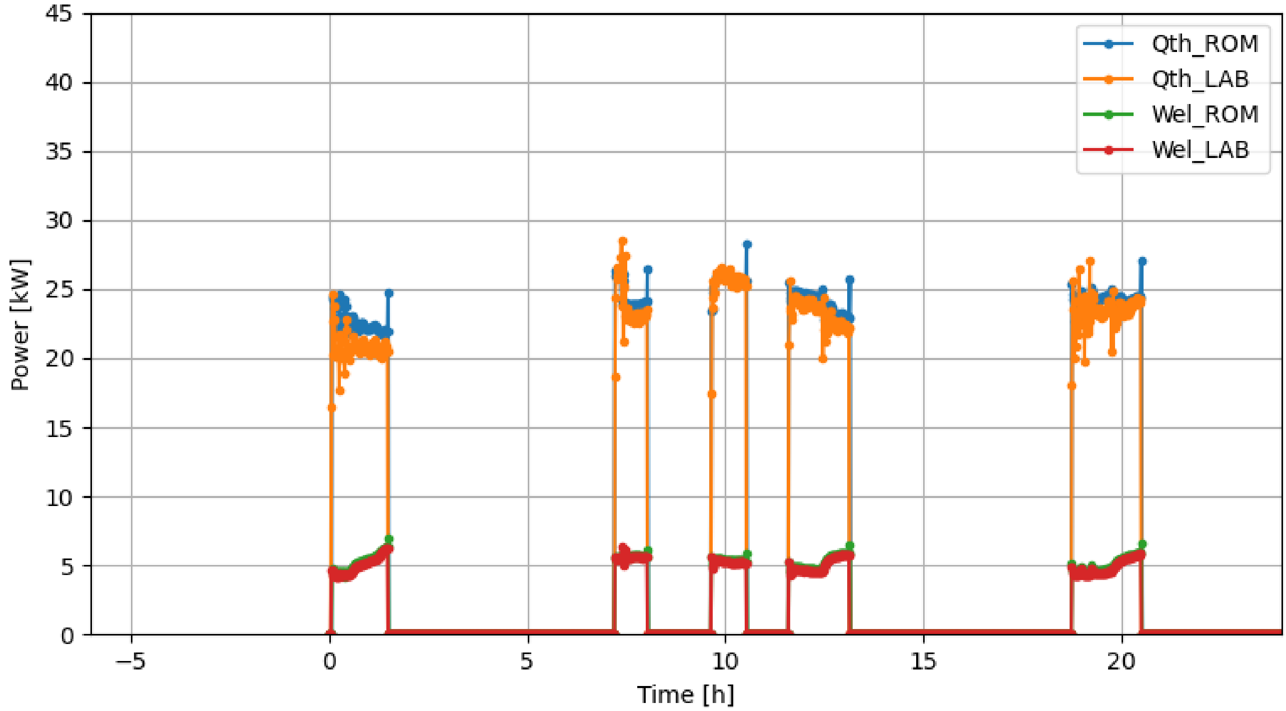

Figure 19 Example of training algorithm. Thermal and electrical power pre- (upper) and post- (lower) training

A similar algorithm was developed to identify the parameters of the PI control. However, this automatic training procedure for the identification of the PI parameters is not implemented in the model yet.

Thermal energy storage model

The core aspects of the model are:

- Development of a novel state-based ROM for TES systems with multiple thermoclines: The simplified model uses a state-based method to track how temperature layers (thermoclines) change in a Thermal Energy Storage (TES) system. It divides the TES process into different states based on how these layers form, move, or disappear, as well as the direction of energy flow (charging or discharging). This approach accurately represents complex temperature changes under different conditions. By smoothly shifting between thermal states, the model provides a clear and precise picture of heat distribution, helping to improve system performance and energy efficiency.

- Achievement of computational efficiency for real-time control applications: The proposed model balances sophistication and computational efficiency, making it suitable for real-time MPC applications. Its streamlined mathematical formulations and efficient state transitions enable rapid computations, addressing a critical need unmet by existing high-fidelity models.

Building's thermal load model

The choice of using an ANN model to calculate the building's thermal space heating load is based on different considerations.

First, in general, the calculation of the space heating thermal load is a task that depends on many different variables, among others, external temperature, solar irradiation, thermal characteristics of the building envelope (e.g. thermal transmittance of envelope elements), internal heating gains associated with the presence of inhabitants and their use of the electrical devices. A physical model would require knowing and setting these parameters to have a meaningful and reliable calculation of building thermal load for space heating. This task is not easy and requires notable effort. Moreover, this approach is quite specific for the considered building or, eventually, for similar buildings. The ANN model, instead, does not require the input of specific quantities characteristic of the considered building.

Second, the building space heating load varies based on the considered granularity, where, in this context, granularity indicates different dimension levels accounted for, spanning from the calculation of the thermal load for space heating of a single room to the entire building. The ANN model works with similar performances regardless of the granularity level considered.

Third, generally, building's space heating systems are controlled by a thermostat. Different configurations are available in the building stock but, the most common, account for the presence of a unique thermostat at the dwelling level or a series of thermostats regulating the thermal energy delivered at room/zone level. This results in the ON-OFF operation of the heating system that is only partially correlated to other parameters affecting the building's space heating thermal demand as external temperature and solar irradiation. This limited correlation, which is an aspect that must be caught at a time resolution lower than 1 hour, makes the identification of a proper model complicated, often resulting in too simplistic and unreliable models. The ANN model ignores the fact that there is a thermostat but simply relies on the data seen during the training.

The ANN models developed can predict space heating thermal loads using for their training only a congruous amount of input data in the past. The fact that the correlation between input and outputs is quite tricky, in comparison to other identification problems, and that the model training should be robust are the main reasons we opted for an ANN model.

Multi-dimensional dynamic programming

Over the last years, EURAC spent significant resources on taking the standard DP formulation and turning it into an advanced DP (ADP), significantly improving the trade-off between computational time and solution quality. The pareto-front between runtime and solution quality has been improved by a factor of 5-10, so for our defined benchmark problem, the ADP is finding satisfactory solutions significantly faster than the standard DP. This has been achieved through a variety of DP enhancement techniques. The two most important ones are briefly described below:

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- Adaptive grid approach: Whereas a standard DP uses a fixed grid of discretisation points, the ADP uses an adaptive grid. In this approach, a first run is done with a very coarse grid (as few as 10 discretisation steps), and then a second grid is created which is much more fine-grained but only encompasses the neighbourhood of the solution found in step 1.
- Smart cutoff criterion: Normally, DP is calculated for a fixed horizon. Our approach terminates the run early if he detects that all solution candidates share the same first step (which is the only step that is actually executed in the real system; all other steps are discarded). This means that the computational time is usually much faster, and the solution quality is the same.

4.4.4 Technology progress and status

To facilitate testing before real-world deployment, a Software-in-the-Loop (SIL) testbench is under development. This test environment allows for validation of the MPC approach under various conditions, ensuring robustness before the system is applied to an operational MFH setting. Key aspects of this work include the development of detailed dynamic models covering building thermal behaviour (TE-11), heat distribution and dissipation mechanisms (radiators, underfloor heating), PV/PVT models, bore fields models, and heat pump models. The individual models are developed using specialised software and are exported as FMU's. Figure 20 shows the graphical user interface of the SiL Testbench.

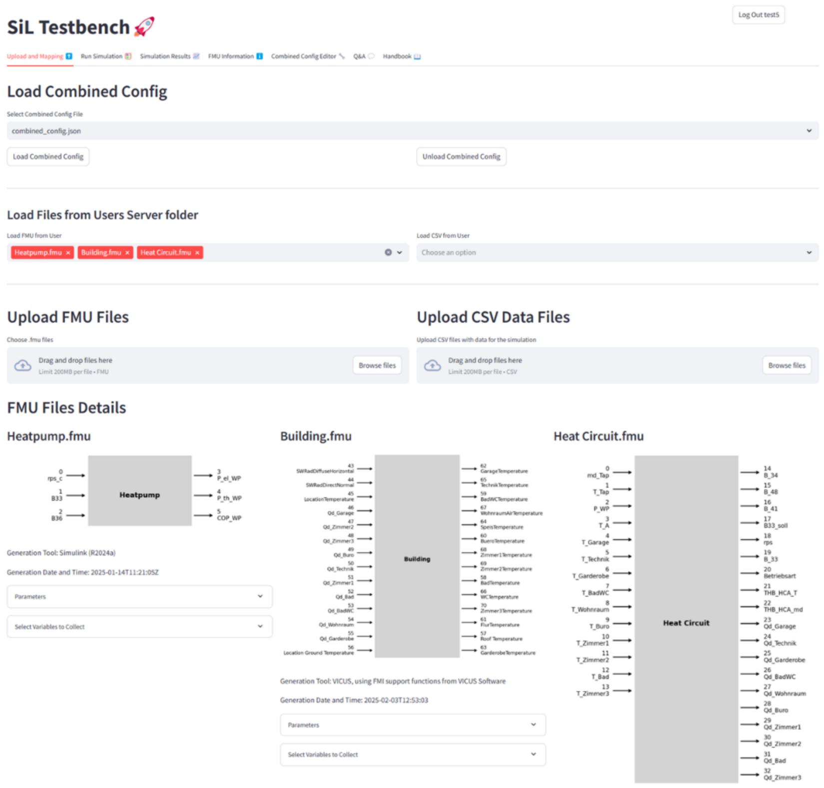

Figure 20 User Interface: Software-in-the-Loop Testbench for MFH-MPC

For monitoring and control of individual thermal zones a single-room heating control module, "Zonenmodul", is being refined to support multi-dwelling monitoring and control. The Zonenmodul interfaces with the heat pumps and acts as gateway to wired and wireless temperature, humidity and VOC sensors as well as to room thermostats. Figure 21 shows a schematical representation of two Zonenmoduls connected to wired and wireless sensors the HP and LAN.

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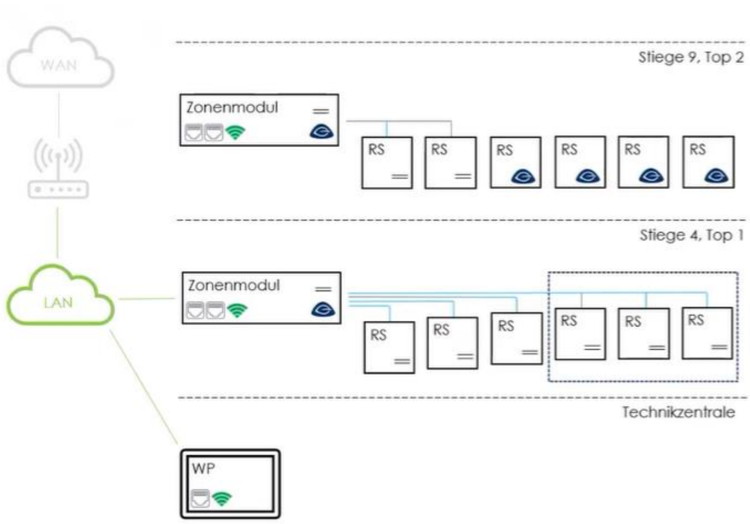

Figure 21 Schematic of Room temperature measurement for multiple thermal zones, via "Zonenmodul"

Reduced-order heat pump model

The reduce order model of the heat pump was tested and validated with both monitoring data and data from laboratory test. The automated training algorithm that allows to associate the thermal power and electrical consumption of the heat pump to the operating conditions proved to be robust. However, what the model is not able to do properly is to identify the correct modulation of the heat pump. The fixed ramps algorithm is a simplification of the real control. This algorithm provides good results for energetic analysis. However, its performance within a control optimisation analysis lacks a bit in accuracy. On the other hand, the PI control algorithm allows to reach better accuracy. Nonetheless, it is up to the user to fine tune the parameters of the PI control in order to get good results.

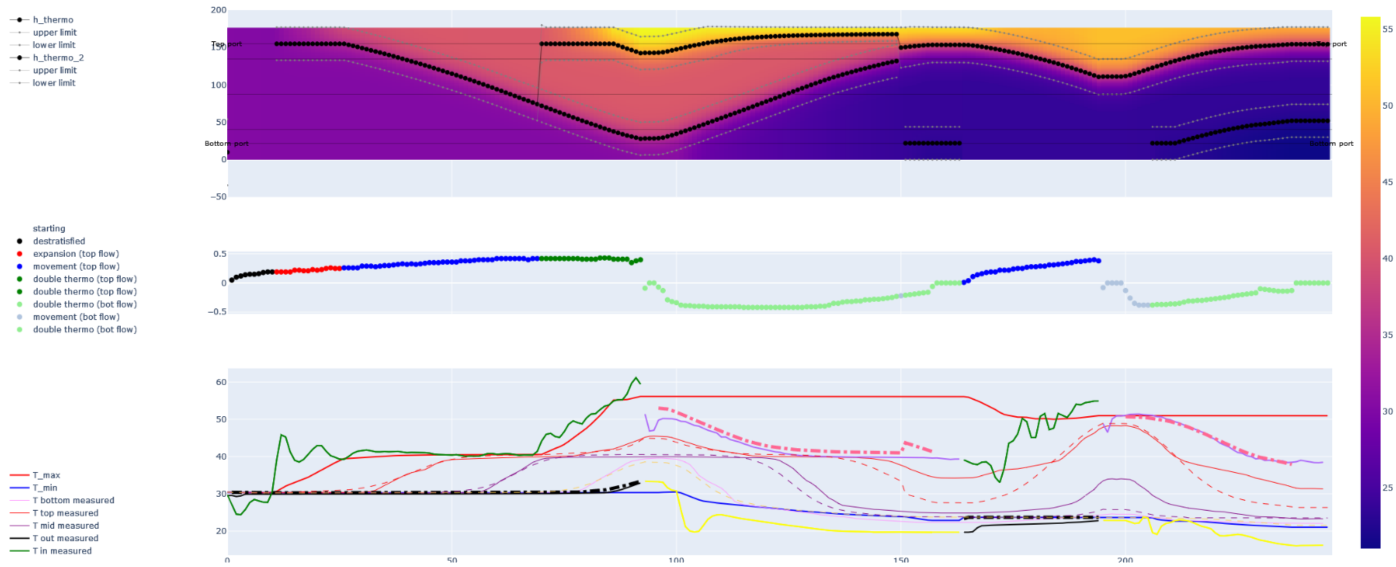

Figure 22 Thermal energy storage model results

Thermal energy storage model

The model was tested and verified against both more complex models using the TRNSYS software [75] and laboratory tests with satisfactory results. Figure 22 shows the model simulating a complex laboratory test with two thermoclines forming on top of one another and disappearing again in multiple different cases. The

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lowest subplot shows both the simulated and observed temperatures at the various sensors in the tank, indicating very good alignment between the model and the data observed in reality in the lab.

However, in certain edge cases with rapid changes in inputs, or simulation timesteps with a lot of mass exchange the model still requires further refinement.

Building's thermal load prediction model

The ANN model predictions, in terms of building indoor temperature and space heating thermal load, have been validated against dynamic simulation results (using TRNSYS as dynamic simulation software) and, partially, against monitored data.

Figure 23 shows the results for 10 days in the winter season for one dwelling of a five-storey small Multi-Family House of 10 dwellings (50 m^2 each), located in Stuttgart. The top figure shows the external temperature (blue), the GHI (yellow), and the electrical consumption associated with the use of electrical devices inside the considered dwelling (black). The middle figure presents the indoor temperature calculated by TRNSYS (black) and predicted by different simulations using ANN models (different colours). The bottom graph shows the space heating thermal load delivered to the considered dwelling calculated by TRNSYS (black) and predicted by different simulations using ANN models (different colours). In addition to that, also the thermal load predicted using a simple model based on the external temperature is also reported (red dashed).

As can be noted in the figure, actually, the ANN model can catch the trends but still presents errors, especially when a sampling time in the range of 5-15 minutes is considered. These errors are generally lower if a night setback is considered in the system control, probably because, with the night setback, during the night, there is a common trend that allows a better identification in the ANN model training.

Moreover, there is a certain variability in the errors between different days (see the higher errors on Dec 10th in the middle and bottom figure).

In addition to that, it should be mentioned that the results present some problems in terms of replicability. If, on one side, a perfect replicability is impossible when dealing with ANN models and with different ANN model trainings, a certain robustness should be ensured to have a stable model. From preliminary studies, it resulted that around 10% of the trainings failed, resulting in unreliable predictions.

Finally, although the ANN model results to be a good choice for the reasons previously mentioned, it must be noted that, in general, it requires a computational time and capacity higher than other models.

Regarding Figure 23, the top graph shows the main inputs considered (external temperature, blue; GHI, yellow; electrical consumption due to appliances, black); the middle graph shows dwelling indoor temperature predicted by TRNSYS model (black) and by different simulations using ANN model (different colours); and the bottom graph shows space heating thermal load predicted by TRNSYS model (black) and by different simulations using ANN model (different colours). The bottom figure also reports the space heating load calculated using a simple model based on external temperature (red dashed line). Granularity considered: dwelling level. Period considered: 1-11 December.

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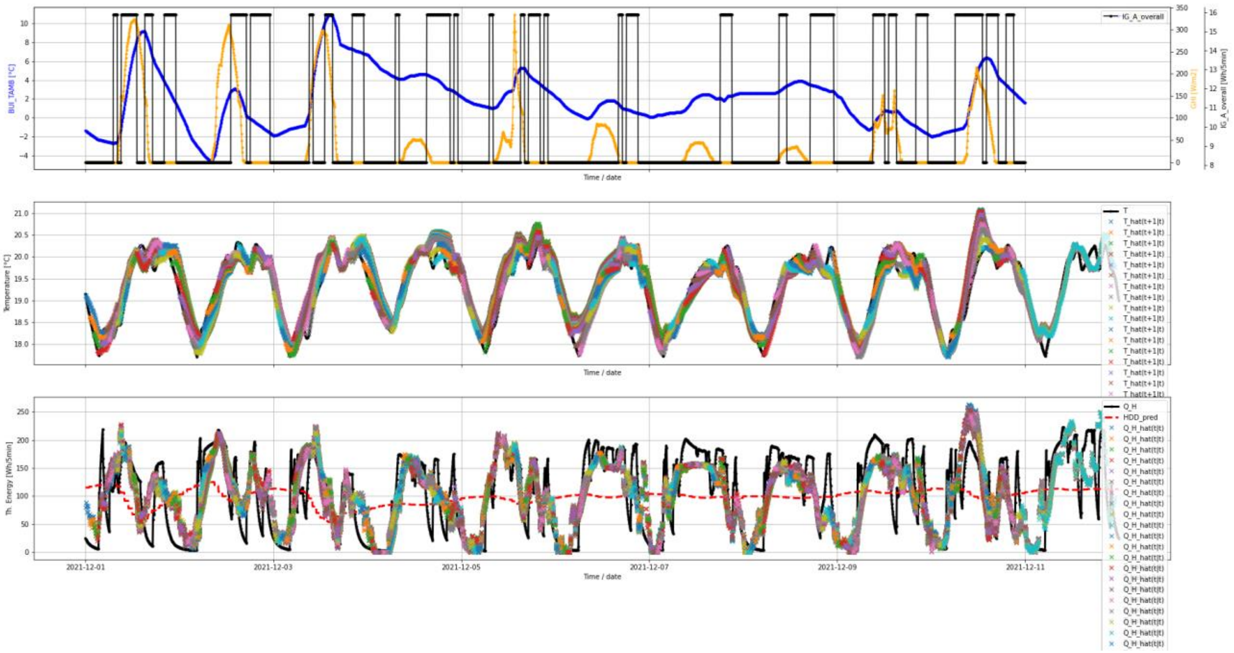

Figure 23 Example of results from ANN model and comparison with ground truth (TRNSYS model).

Multi-dimensional Dynamic Programming

The 1D technology is mature and tested in various simulation settings on multiple different optimisation problems. We were also able to measure the improvements of the various DP enhancements. Work is in progress to publish these findings. The current work focuses on expanding the approach to work in multiple dimensions and further standardising the Python package used so that it might eventually also be made available for external researchers and partners.

4.4.5 Ongoing work

As a part of the ongoing work for the MPC system the following points were identified:

- Develop/adapt Models tailored for control (reduced order/simplified)
  - Based on findings from WP5 – "Deployment & demonstration in real cases", WP2 – "Electrified thermal energy demand integrated solutions & demonstration strategy", TE-11.
- Formulate OCP (including pre and post processing of monitoring data and set points).
- Setup/parametrise models in SIL-Testbench.
- Test MPC for MFH in SIL-Testbench.
- Develop communication infrastructure.
- Deploy at FR1 (iDM).
- Comparison of the two approaches with SiL.

Reduced-order heat pump model

A training algorithm for the identification of the parameters of the PI control is under development. However, this automatic training procedure is not implemented in the model yet. In the future this training algorithm will be further developed and included in the model. The main idea of this improvement is to tech to the model how to modulate the compressor speed adequately. In this way it will no longer be up to the user to fine tune the model in order to get a good correspondence between the modulation performed by the reduced order model and the modulation performed by the real machine.

Thermal energy storage tank

The model already fully operational and being used in various applications in the laboratory for tests. The main issue that remains to be properly addressed in the future is to thoroughly implement feedback from measured values in the lab. Over time, even the best models will slowly start to diverge from the values observed in the laboratory. The challenge is how and when to update the model status based on measured values.

This is no trivial task, as the lab usually does not show the entire water column in the tank but just a few measurement points over time. The challenge is how to estimate the parameters that the model uses internally (the temperatures as well as the height and the width of the thermocline) based on the 3-4 measured temperatures that are available.

Building's thermal load prediction model

The ANN model results have been validated against dynamic simulations performed in TRNSYS and, to a limited extent, against monitored data. Further analysis and validation should be done, especially against monitored data and especially for cooling operations, where, until now, fewer checks have been done.

One aspect that deserves further analysis is related to the accuracy of the prediction of both indoor temperature and space heating thermal load. In fact, both quantities present errors, especially considering a time resolution lower than 1 hour and in the range of 5 – 15 minutes. These errors are generally lower if a night setback is considered, making reasonable to investigate, in particular, the case where a night setback is not considered.

Another aspect to be investigated more regards the replicability of the results, in particular, possible improvements should be evaluated to limit the possibility of having a failed training of the model, resulting in notably lower performance in terms of accuracy of the predicted quantity. Based on some preliminary tests performed, actually, the probability of having a failed training is in the range of 10%.

Moreover, it would be useful to understand the possibility of also including the indoor temperature setpoint in the inputs. This would allow understanding the amount of energy that could be temporarily stored in the building, enabling the evaluation of load shifting in pre-defined periods according to different purposes (e.g., increase self-consumption or exploit flexibility services to the local Distributor System Operator (DSO)).

Finally, it would be interesting to investigate the possibility of changing the actual settings of the ANN models or the usage of different models (e.g., Resistor-Capacitor (RC) or hybrid (e.g., physics-informed neural network) models) to obtain similar results in terms of accuracy, with eventually simpler models, able to run faster also on hardware installed locally with a limited computation capacity.

Multi-dimensional dynamic programming

In the short term, the goal is to expand the methodology and enhancements to reliably also work in an nD context. In the medium term, the focus will switch to applying this methodology to more complex use cases where multiple dimensions are required and explore hybrid approaches, where the ADP finds a preliminary solution, and then a heuristic or metaheuristic searches the immediate neighbourhood of the ADP solution looking for further optimisation opportunities.

The next steps that EURAC is currently focusing are as follows:

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- Add the refinements to the models and algorithms as described above
- Validate the model against TRNSYS types
- Create system model in Python and TRNSYS for FR5 and validate them against each other
- Develop a fully functional MPC in a simulation environment with TRNSYS in the loop (TiTLoop)
- Implement the solution on an edge device deployed at FR5.

4.4.6 Structural view and integration points

A structural representation of TE13's interactions with other META BUILD technologies and services is shown in Figure 24.

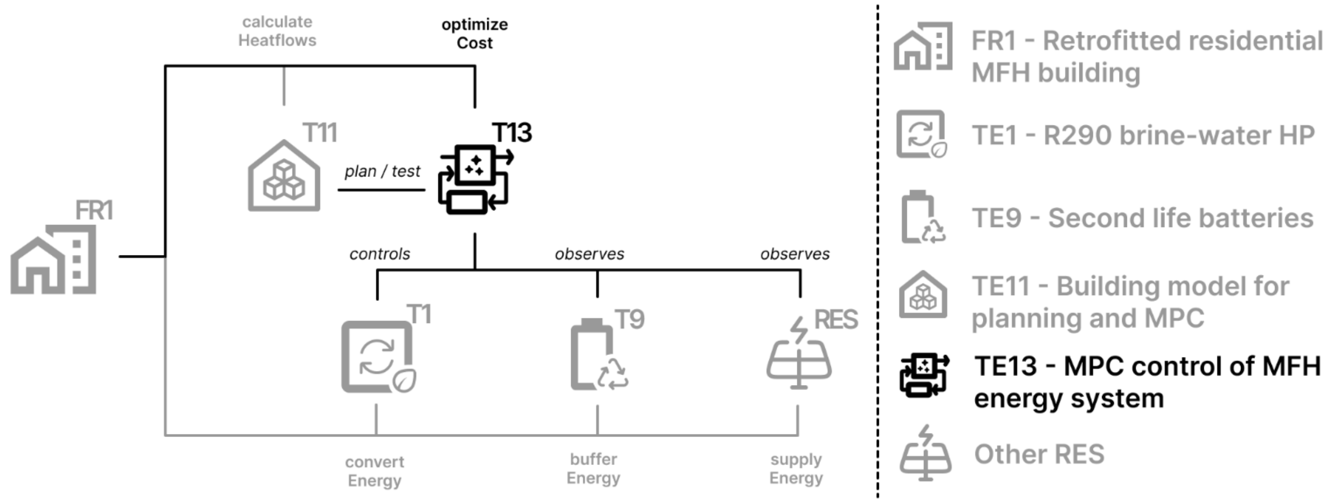

Figure 24 Interaction of MPC control with other META BUILD technologies.

Additionally, to the technologies depicted in Figure 24 the following technologies and services are required for TE13:

- API to Day-Ahead pricing data of energy provider for dynamic cost optimisation.
- Indoor temperature sensors in each apartment/thermal zone.
- API to weather data provider.
- Forecast of local el. consumption / RE production
- Actuators to control radiators or underfloor heating devices per thermal zone.

4.4.7 Interoperability considerations and preliminary findings

- An API is to be established to send predictive control set points in the heat pump and building energy management system.
- The models for SiL and MPC need to be well documented for effective model exchange.
- Some interface between devices (HPS, BEMS, PV inverter, battery management, sensors) might need to be established based on established standards, e.g., IEC 61158 [94].

4.5 Demand Response, Grid interaction & Flexibility Planning

4.5.1 Overview

The increasing adoption of heat pumps across the EU, the growing share of intermittent renewable energy sources and the electrification of heating, present new challenges and opportunities for the electricity grid. As the EU energy landscape gradually shifts toward decarbonisation, residential electricity demand is becoming more dynamic, requiring novel approaches to demand-side flexibility and grid optimisation. This transformation brings new challenges for maintaining grid stability yet also offers significant opportunities to optimise electricity demand and reduce costs through intelligent flexibility strategies. The proposed framework addresses these challenges by integrating three key elements: predictive power market modelling, market-driven automation and automated demand response (DR) strategies. This comprehensive approach aims to transform heat pumps from passive energy consumers into active, flexible assets capable of responding dynamically to price fluctuations and renewable generation forecasts.

By combining these technologies, the framework seeks to achieve multiple objectives. First, it strives to reduce electricity costs for consumers by scheduling heat pump operation during periods of lower market prices, as much as possible. Secondly, it envisions to enhance grid stability by shifting heating loads away from peak demand periods, thereby reducing congestion. Finally, the framework aspires to improve renewable energy utilisation by aligning heat pump operation with periods of excess generation, which would otherwise go underutilised. The integration of advanced analytics, IoT-enabled control mechanisms and automated DR strategies, ultimately position this framework as a practical and effective tool to support Europe's decarbonisation efforts.

4.5.1.1 The Need for Demand Flexibility in a Decarbonised Grid

The decarbonisation of Europe’s energy system heavily depends on the electrification of heating, with heat pumps playing a potentially vital role in replacing fossil-fuel-based systems. While this shift offers significant environmental benefits, it also presents considerable challenges for power system operators and market participants. The widespread electrification of heating amplifies residential electricity demand, particularly in winter when heating loads peak. Consequently, new demand peaks are likely to emerge, especially during morning and evening hours when heat pump usage coincides with other domestic energy loads, such as electric vehicle charging and household appliances. This evolving demand profile introduces considerable stress on the electricity grid, especially when combined with the variability inherent in renewable generation. As wind and solar output fluctuates, periods of excess supply and sudden price surges become increasingly frequent, making traditional grid-balancing methods less effective.

Without intelligent demand-side flexibility strategies, several risks arise. Higher peak electricity prices may result from increased winter demand, placing greater financial strain on households. At the same time, grid stress may intensify as electrification expands, amplifying volatility in both the wholesale and retail electricity markets. Moreover, renewable energy produced during off-peak hours may go underutilised if residential heating loads remain fixed to traditional schedules.

To mitigate these risks, the proposed framework introduces a structured methodology for transforming heat pumps into active, grid-responsive assets. By dynamically adjusting heat pump operation to align with periods of low prices and high renewable generation, the framework enables a more flexible, resilient and cost-effective energy landscape.

4.5.1.2 The focus on Heat Pumps of demand-side management

While the suggested framework is designed to be as open and inclusive as possible of various assets and installations, Heat Pumps are uniquely suited to automated demand response for several reasons.

One of the most notable strengths of heat pumps lies in their thermal energy storage capability. Unlike conventional electrical appliances, heat pumps can pre-heat or pre-cool a building, effectively storing thermal energy in the building's structure or dedicated thermal storage systems. This inherent flexibility allows heating loads to be shifted from peak hours without compromising indoor comfort. Moreover, heat pumps represent a significant share of residential energy consumption, making them a valuable target for grid optimisation strategies. Even modest adjustments to heat pump operation can translate into measurable reductions in overall grid demand during peak hours. Additionally, because heat pumps are major contributors to household electricity costs, consumers stand to benefit substantially from strategic load shifting. Additionally, modern heat pumps are increasingly equipped with smart control capabilities, further enhancing their suitability for demand-side flexibility. By integrating market signals, weather forecasts, and household heating demand data, smart control algorithms can optimise heat pump performance to minimise costs while maintaining indoor comfort. These algorithms can dynamically adjust factors such as setpoint temperatures, compressor speed and heating schedules, ensuring efficient energy usage.

Despite their potential, several challenges must be addressed to fully harness the flexibility of heat pumps. User adoption remains a key concern, as some residents may resist automated heating controls due to concerns about comfort or uncertainty regarding cost savings. Additionally, device compatibility issues can arise since different heat pump manufacturers may rely on proprietary communication protocols. Finally, market volatility presents another challenge, as fluctuating electricity prices increase the complexity of predicting optimal load-shifting schedules.

To address these challenges, the proposed framework emphasises user-centric automation, giving households the flexibility to define their preferred comfort ranges. Additionally, the system leverages standardised API protocols to ensure compatibility with diverse heat pump models. By combining these elements with hybrid forecasting models that predict both market prices and heating demand, the framework aims to deliver an adaptable, efficient and user-friendly solution for heat pump automation.

4.5.1.3 Moving from Passive Loads to Active Grid Participants

An innovative aspect of the proposed framework lies in its ability to transform heat pumps from passive energy consumers into active grid participants. This transformation supports both explicit and implicit DR programs, ensuring flexible load control with minimal consumer intervention.

In explicit DR programs, consumers are directly incentivised to adjust their electricity consumption in response to financial rewards. Under this model, utilities or aggregators send price signals encouraging residents to reduce heating demand during peak periods or shift consumption to off-peak hours. In contrast, implicit demand response programs operate outside energy market operations (e.g., Time-of-Use tariffs), without requiring active user participation.

This dual compatibility of the proposed framework is particularly important, since flexibility, demand-side management and dynamic pricing are essential in the transition towards a decarbonised future [15]:

- Flexibility Needs: The EU's electricity system is evolving, driven by a rise in renewable energy sources (like wind and solar). This increase in intermittent power generation calls for more flexibility to balance supply and demand. Flexibility is primarily needed from consumer behaviour, energy storage and demand-side response, where consumers adjust their energy usage based on price signals to help manage grid stability.

- Demand-Side Management (DSM): Involves incentivising consumers, particularly residential, to adjust their consumption during peak demand or when renewable energy is abundant. The use of smart meters and dynamic pricing contracts is key to enabling demand-side response.
- Dynamic Pricing: This pricing model adjusts rates based on real-time market conditions, incentivising consumers to shift their consumption to times when energy is cheaper and more abundant.

Different European countries have adopted various approaches to DSM, dynamic pricing and flexibility, based on their local energy markets, regulations and infrastructure capabilities.

- Smart Meter Deployment: The use of smart meters and dynamic pricing contracts is key to enabling demand-side response. However, barriers such as limited smart meter deployment and regulatory constraints hinder wider adoption.
- Dynamic Pricing Models: Some countries have made dynamic pricing widely available, while others lag behind. For example, Denmark, Germany, Sweden, and the Netherlands have a variety of flexible pricing contracts available, including real-time pricing, critical peak pricing, and hybrid models that combine fixed and variable pricing elements. These options allow consumers to adjust their consumption to take advantage of lower prices during high renewable energy production times. In contrast, France, Ireland, Greece, and Portugal have either limited or no access to dynamic-price contracts despite EU regulations requiring them, due to barriers such as slow smart meter rollouts and price interventions that impede market flexibility.
- Consumer Engagement: Countries like Sweden have introduced incentives and educational campaigns to encourage consumers to shift their energy usage during peak renewable generation periods, helping them save money and contribute to grid stability. On the other hand, in France, dynamic contracts were briefly available but were withdrawn due to market instability caused by the energy crisis. This highlights the challenges of integrating flexible pricing in markets under financial stress.

Therefore, while some European countries are leading the way in flexibility, demand-side management and dynamic pricing, others face significant barriers related to smart meter deployment, regulatory frameworks and market conditions. Efforts to standardise and incentivise dynamic pricing across the EU remain critical for meeting the region's decarbonisation goals.

Taking into account the recent policy insights [16], the proposed automated demand-side management and flexibility planning tool can assist in:

- Decarbonisation, by enabling greater consumer participation in demand response, reducing reliance on fossil-fuel-based power plants and integrating more renewable energy into the grid.
- Market efficiency, by aligning residential energy consumption with wholesale market signals, fostering dynamic pricing adoption and enhancing retail competition.
- Grid stability, by mitigating peak-hour congestion, improving system flexibility and reducing the costs associated with balancing and congestion management.

Our proposed framework aligns with the urgent need for flexibility, the importance of dynamic pricing models and the role of consumer engagement in ensuring a resilient and decarbonised EU energy system.

4.5.1.4 Initial Methodological Requirements: Addressing Gaps in Automated residential HP DR domain

Despite the growing potential of automated demand-side management, several gaps remain in the effective implementation of residential heat pump DR systems.

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From a technical perspective, electricity price volatility and inconsistent renewable generation patterns introduce significant uncertainty. Without robust forecasting models, optimising heat pump operation becomes difficult. To address this, the proposed framework integrates hybrid AI models that combine HP data with market trend analysis, improving load-shifting precision.

IoT and interoperability challenges also present obstacles, as heat pumps from various manufacturers often rely on incompatible communication protocols. The framework mitigates this by adopting Restful API integration, allowing devices to communicate seamlessly with the control system.

Behavioural factors also play a role, as consumer awareness of dynamic pricing benefits remains limited. Some residents may express concerns about potential discomfort resulting from automated temperature adjustments. The framework addresses these concerns by providing clear, real-time feedback through user dashboards, which illustrate the cost savings and comfort impacts of each automated control action.

By integrating adaptive forecasting, standardised communication protocols, and transparent user interfaces, the proposed system aims to empower households to contribute meaningfully to grid flexibility while ensuring comfort and cost savings.

The resulting framework presents a comprehensive and forward-looking strategy to manage heat pump loads effectively, supporting Europe's ambitious climate and energy targets.

4.5.2 Core technology aspects

4.5.2.1 High-Level Framework Scope: Managed Loads

The proposed framework introduces a managed load strategy, emphasising intelligent load-shifting of heat pumps based on predictive market signals. By leveraging advanced forecasting models and automated DR, the system ultimately ensures that HPs operate at optimal times without compromising user comfort.

A key vision of the suggested framework is its ability to dynamically adjust HP operation in response to market price fluctuations, utilising real-time HP monitoring and day-ahead market (DAM) forecasts. The methodology involves shifting HP load in response to expected price trends and ensuring that HP usage aligns with grid-friendly periods.

4.5.2.2 Overview of Load-Shifting Mechanism

The mechanism is part of a HEMS which monitors, models and forecasts home energy assets, including primarily HPs and perhaps PV systems and storage, if available. Monitoring is being done by using behind-the-meter IoT sensors and API connections for real-time consumption tracking. The main functions of the load-shifting mechanism are the following:

- Ramp-Up During Low-Cost Periods (Pre-Heating Strategy):
    - The system pre-heats (residential) buildings during midday hours, leveraging excess solar generation and ensuring energy is stored thermally rather than relying on costly electricity in peak demand hours.
    - This phase aligns with low DAM prices, which typically occur when solar PV generation peaks and grid supply exceeds demand.
    - The predictive model calculates expected energy requirements, adjusting heat pump runtime and perhaps flow temperature to maximise efficiency while ensuring stored thermal comfort.
- Ramp-Down During Peak Cost Periods:

    - In the evening, as electricity prices rise due to high demand, HPs reduce operation to avoid consuming expensive electricity.
    - The stored heat from earlier operation maintains indoor temperature within pre-set comfort thresholds.
    - The system continuously monitors indoor climate conditions, ensuring that energy reductions do not jeopardise user comfort.

- Dynamic Adjustments Based on near Real-Time Pricing:
    - If market forecasts deviate significantly due to unexpected price volatility, the framework dynamically adjusts the HP schedule.
    - This ensures that residential heating is optimised both economically and in terms of grid efficiency.

This above load-shifting initial methodology enhances flexibility, allowing both energy consumers and utilities to benefit from intelligent scheduling, while supporting grid stability and decarbonisation goals.

4.5.2.3 Home Energy Management System

The HEMS acts as the central monitoring and control unit, collecting data from:

- IoT-enabled smart meters, tracking household energy consumption in real time.
- Environmental sensors, monitoring indoor air quality, humidity and temperature fluctuations.
- Heat pump controllers, regulating operation based on modelled HP behaviour and forecasted electricity prices and load-shifting strategies.
- External data sources, including weather forecasts and market price trends, to anticipate future energy needs and optimal operating windows.

HEMS integrates with cloud-based analytics, ensuring that data processing and decision-making are scalable and secure. The real-time control and monitoring capabilities of HEMS allow users and utilities to visualise and adjust heat pump operation dynamically.

4.5.2.4 Wholesale Power Market Forecasting

The framework incorporates a machine learning-driven power market forecasting model designed to:

- Predict Day-Ahead Market (DAM) electricity prices based on historical market trends, renewable generation forecasts and grid conditions.
- Provide hourly price forecasts for the next 24 hours, enabling optimised scheduling of residential heat pumps.
- Detect high-price volatility scenarios, allowing for rapid response to unexpected market fluctuations.

To enhance forecasting accuracy, the system employs:

- Time-series models such as XGBoost [61] and LSTM [76], trained on market clearing prices, system load forecasts and renewable energy availability, among others.
- Anomaly detection algorithms that identify market shocks or unexpected demand surges.
- Automated data ingestion pipelines that pull real-time data from market operators and system operators.

These market forecasts serve as input signals for the HEMS and heat pump control module, ensuring that HPs align their operation with cost-efficient time slots.

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4.5.2.5 Advanced Predictive Models for Energy Optimisation

The framework envisages deploying a suite of AI-driven predictive models to enhance energy flexibility and optimise load shifting. These include:

- Heat Demand Forecasting Models:
  - Predict hourly heating demand for each residential unit based on occupancy patterns, thermal mass and local weather conditions.
  - Optimise heat pump runtime to pre-emptively store heat when market conditions are favourable.
- Market Price Prediction Models:
  - Forecast DAM price trends and identify optimal hours for HP operation.
  - Adjust load schedules in real time based on forecast accuracy.
- Renewable Generation Forecasting:
  - Estimate local solar availability to synchronise HP operation with peak renewable supply.
  - Minimise operation during low-renewable, high-carbon grid conditions.

These predictive models allow for smarter, cost-efficient and sustainable operation of HPs, balancing user comfort with economic incentives.

4.5.2.6 Flexibility Impact Analysis

The Flexibility Impact Analysis module investigates and quantifies the potential economic and environmental benefits of load shifting for both individual households and utilities.

- For Residential Consumers:
  - Lower electricity bills due to intelligent scheduling based on market signals.
  - Increased control and transparency over energy usage through real-time monitoring dashboards.
- For Utilities and Aggregators:
  - Ability to aggregate residential saved loads for market participation.
  - Enhanced grid stability by shifting demand away from peak congestion periods.

The system should simulate different load-shifting strategies and compare them based on:

- Total energy cost savings per household.
- Peak demand reduction impact on the grid.
- CO_2 emissions reduction due to increased renewable energy utilisation.

This data-driven analysis ensures that all stakeholders benefit from the automated demand response strategy.

4.5.2.7 Tenant/Aggregator Dashboard

The Tenant and Aggregator Dashboard provides a user-friendly interface for:

- Monitoring household energy consumption in real time.
- Tracking savings and energy flexibility potential.

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- Adjusting heat pump preferences based on personal comfort needs.
- Receiving dynamic pricing notifications, alerting users to favourable operational windows.

For utilities and aggregators, the dashboard can offer:

- Aggregated demand response analytics, showing load-shifting participation levels.
- Market trading insights, helping utilities optimise bidding strategies for demand flexibility.
- Historical energy consumption reports, enabling customised incentives for participants.

This dashboard can act as the central user interface, empowering both households and market operators to make informed energy decisions.

4.5.2.8 Summary of Core Technology Aspects

An outline of the fundamental technological components of the framework includes the following:

- Intelligent load-shifting strategies for heat pumps to align with market price fluctuations.
- Advanced predictive modelling for DAM price forecasting, energy demand estimation and renewable integration.
- A cloud-based HEMS with real-time monitoring and control capabilities.
- A Flexibility Impact Analysis module quantifying the financial and environmental benefits of demand response.
- An interactive dashboard empowering consumers and utilities to make informed energy decisions.

The integration of machine learning, IoT-enabled control and market-driven automation makes this framework a powerful and scalable tool for optimising residential heating loads, supporting grid stability and accelerating the transition to a carbon-neutral energy system.

4.5.3 Starting status, description and constraints

4.5.3.1 Home Energy Management System

The HEMS is the core component for managing energy loads, providing monitoring and control over residential assets, including Heat Pumps, PV systems, and various IoT sensors that collect environmental data. The initial design of the system is focused on flexibility and scalability, allowing it to integrate seamlessly into existing homes as well as new builds with renewable energy systems.

Asset Monitoring

The HEMS relies heavily on (near) real-time data collected from a range of possible asset monitoring devices:

- Heat Pumps: These are continuously monitored to track energy consumption, thermal demand and operation efficiency.
- PV Inverters: These are used to track energy production from solar panels, ensuring that the system optimises the use of self-generated electricity before tapping into grid power.
- IoT Sensors: A suite of sensors collects data on indoor air quality, temperature (°C) and outdoor environmental conditions. These sensors are vital for maintaining optimal home comfort levels while ensuring efficient energy consumption.

Data from these assets is ingested by the HEMS, which processes and analyses the information in real time, feeding it into the system's decision-making algorithms.

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Data Granularity

The system collects data at various intervals, allowing for a highly granular view of energy usage and environmental conditions:

- HP Load (kWh): Monitored on a per-minute basis, providing accurate tracking of energy consumption for heating and cooling purposes.
- PV Generation (kW): Tracked at 15-minute intervals to ensure synchronisation with energy consumption and efficient use of generated electricity.
- Indoor/Outdoor Temperatures (°C): Both indoor and outdoor temperatures are captured at 15-minute intervals, helping the system make real-time adjustments based on thermal comfort requirements.

This granularity ensures that the system can make highly responsive adjustments, optimising both economic savings and comfort without overcomplicating decision-making or overwhelming system resources.

Control Mechanisms

The control mechanism within the HEMS allows for the dynamic adjustment of HP operations to align with real-time energy prices and comfort parameters. The control logic works in tandem with predictive algorithms to:

- Ramp up or down HP operation based on market price forecasts (pre-heating during low-cost hours and reducing consumption during peak hours).
- Adjust set-point temperatures and control air quality based on comfort thresholds, ensuring that occupants experience minimal discomfort during dynamic load shifting.
- Coordinate PV usage by utilising self-generated energy during low-price periods and supplementing from the grid when necessary.

This predictive control framework ensures that residential energy assets are operated in the most cost-effective and grid-friendly manner, ensuring maximum benefits for both users and utilities.

HEMS Architecture

The HEMS architecture is designed to be modular and scalable, consisting of the following key components:

- Data Collection Layer: Integrates IoT sensors and asset monitoring systems to collect near real-time data from HPs, PV systems and environmental sensors.
- Data Processing Layer: Involves near real-time data analysis, preprocessing (e.g., cleaning, normalisation) and storage (in databases or cloud platforms).
- Control Layer: Contains the decision-making algorithms that analyse incoming data and provide actionable commands to devices like heat pumps or thermostats.
- User Interface Layer: Provides dashboards that allow users to monitor energy usage, view performance data and adjust settings for greater comfort or efficiency.

The cloud-based approach allows the system to scale from a single residence to larger clusters of buildings while maintaining real-time responsiveness.

4.5.3.2 Wholesale Power Market Forecasting

The Wholesale Power Market Forecasting (WPMS) module plays a critical role in predicting future electricity prices, enabling the HEMS to optimise the operation of HPs and other energy assets.

Feature Engineering

To build accurate forecasting models, several features are incorporated into the system:

- Power Grid Data: The model incorporates forecasts for solar, wind and hydro generation into the model to understand the impact of renewable energy availability on electricity prices. Additionally, the model integrates interconnectivity data between neighbouring countries. This information provides insights into potential grid imbalances, helping to predict price spikes or drops due to cross-border energy flows.
- Market Historical Data: Hourly market data from previous Day-Ahead Market (DAM) price sessions informs the model, identifying seasonal patterns and pricing trends.

Model Training

The model training process includes the use of XGBoost and other machine learning algorithms to forecast electricity prices:

- XGBoost Trained on historical DAM Data: The model is trained on historical DAM price data, so that it demonstrates low Mean Absolute Error (MAE) and provides reliable price predictions.
- Feature Optimisation: The model includes features that account for market volatility, energy generation patterns and geopolitical events.

It is essential that the model maintains forecasting accuracy by incorporating geopolitical risk indices into the prediction pipeline and enable the model to predict price surges caused by supply disruptions, thus enhancing its robustness and adaptability in volatile markets.

4.5.3.3 Flexibility Impact Analysis

The Flexibility Impact Analysis (FIA) module evaluates the financial and operational impact of load-shifting and demand response strategies on both consumers and utilities.

Load-Shifting

One of the central features of the tool is its ability to shift heating loads based on market prices.

- Indicative Load-Shifting Savings Formula:

  $$\text{Savings} = E_{\text{shifted}} \times (\text{DAM}_{\text{high}} - \text{DAM}_{\text{low}}) - \text{Comfort Loss Penalty}$$

  Where:

  E_{shifted} is the energy shifted during off-peak periods.

  DAM_{high} and DAM_{low} represent the high and low DAM prices during peak and off-peak hours, respectively.

  Comfort Loss Penalty accounts for the user’s tolerance in terms of indoor temperature fluctuations.

- Comfort Threshold: The system accounts for user comfort by allowing a ±1.5°C fluctuation in temperature, which is tolerated by 80% of users. The penalty is applied when this threshold is exceeded, ensuring that the comfort level is maintained during load-shifting operations.

Load-Shedding

- The system could increase also support load-shedding, where aggregators can reduce demand during peak periods, e.g. During a load reduction in demand, aggregators can increase earnings, helping to maintain grid stability.

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- Incentive Tracking: The HEMS dashboard tracks load-shedding rewards, providing real-time feedback and incentives for users who participate in peak demand reduction.

Dashboard Update

Preliminary updates to the dashboard include:

- Load-Shedding Alerts: The system notifies users and utilities when the potential for load-shedding arises, providing clear instructions for participation.
- Incentive Tracking: Users can view their accumulated incentives for participation in load-shedding, encouraging ongoing engagement with the demand-response system.

4.5.4 Technology progress and ongoing work

The development and implementation of the HEMS and the Wholesale Energy Market System (WEMS) have advanced steadily, progressing through multiple experimental phases designed to validate technical feasibility and improve system performance. Significant progress has been achieved in enhancing data integration, refining predictive analytics and designing control mechanisms. This section outlines the milestones achieved thus far and identifies key future steps to further improve the framework's capabilities, ensuring efficient Demand Side Management (DSM) and optimised heat pump control strategies.

4.5.4.1 Experimentation with Monitoring and Controlling Mechanisms for Heat Pumps

Developing reliable mechanisms for monitoring and controlling residential heat pumps has been a key priority for the framework. To achieve effective demand response integration, the project has concentrated on both hardware-based sensing solutions and software-driven monitoring and control strategies. These efforts aim to ensure that heat pump operation is optimised in response to market signals, weather forecasts and comfort thresholds.

Progress has been made in implementing real-time monitoring systems that track key heat pump metrics such as energy consumption, runtime behaviour and setpoint temperatures. IoT-based data acquisition methods have been integrated to enable continuous monitoring, ensuring that heat pump performance is analysed dynamically. Additionally, early-stage control mechanisms have been developed to enable load shifting strategies, where heat pump operation is adjusted based on predicted market prices. To further optimise performance, the system has been designed to incorporate external weather data and indoor air quality metrics, allowing predictive models to anticipate heating demand without compromising thermal comfort. These improvements aim to ensure that HPs operate efficiently while respecting residents' comfort boundaries.

Progress to date includes the successful deployment of a cloud-based control platform, enabling secure two-way communication between heat pumps and the management system. Early versions of predictive models have also been developed, capable of forecasting heating demand based on indoor temperature trends and environmental conditions. Future efforts will focus on refining these capabilities. Planned activities include expanding the platform's capabilities to support on/off control, setpoint adjustments, and dynamic compressor modulation using manufacturer-specific APIs. These improvements will strengthen the system's capacity to dynamically control HP operations in real-world conditions.

4.5.4.2 Investigation of PV API Communications

The integration of solar PV systems into the HEMS plays a crucial role in enabling efficient self-consumption and optimizing grid interactions. To ensure PV-generated electricity is effectively utilised, the framework has

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focused on exploring data exchange protocols that facilitate near real-time PV monitoring and coordinated load shifting strategies.

Initial efforts have centred on developing API-based communication layers that extract detailed information on PV generation, enabling the system to assess when self-generated electricity can be used directly rather than relying on grid consumption. These communication protocols synchronise PV generation forecasts with residential energy demand patterns, ensuring that heat pump operation aligns with surplus renewable energy availability. An additional area of exploration has involved implementing automated dispatch mechanisms capable of prioritising self-consumption over grid import. By dynamically allocating PV-generated electricity to meet heating needs during periods of abundant solar generation, this mechanism reduces reliance on grid electricity, especially during peak market hours. To date, the project has successfully identified API integration opportunities with PV inverter systems, allowing real-time PV generation data to flow directly into the HEMS. Additionally, preliminary designs for an automated dispatch mechanism have demonstrated potential for improving energy self-sufficiency.

Moving forward, future development will focus on refining forecasting models that predict PV generation using weather data and historical performance records. Enhanced load-balancing algorithms are also planned to dynamically allocate PV energy across household consumption and grid export, further optimising the system's flexibility and efficiency.

4.5.4.3 Selection of IoT Sensors and initial deployment

The early phase of implementation included selecting the appropriate IoT sensors to monitor HPs, PV inverters and environmental parameters. These sensors should provide real-time data crucial for:

- Heat pump performance evaluation (energy consumption, temperature control efficiency).
- Indoor air quality monitoring (temperature, humidity, CO_2 levels, etc.).
- Smart thermostat control, ensuring optimal comfort with minimal energy use.

Progress Achieved

- Selection of wireless IoT sensor networks capable of reporting load data.
- Design of a secure data transmission mechanism to ensure low-latency monitoring and control.
- Set-up of an automated monitoring system, which identifies total consumption, HP load and local PV generation.

Future Steps

- Proceed with sensor deployment in real-life contexts for testing.
- Investigate data fusion techniques that merge multiple sensor streams into a single analytics model for improved decision-making.
- Enhance privacy measures through edge computing solutions that process data locally before cloud transmission.

4.5.4.4 Initial Design of Baseline Modelling and Predictive Analytics for Home Energy Assets

To support effective decision-making and load control strategies, the framework's analytics engine is being designed to provide detailed insights into household energy consumption, heat pump performance and PV generation trends.

The analytics framework utilises data streams gathered from heat pump communication interfaces, PV inverters and smart thermostats to model typical household energy patterns. Early efforts have focused on

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exploring baseline algorithms capable of predicting HP consumption trends and identifying PV output fluctuations based on environmental conditions. In parallel, investigations have explored the potential of load classification models that differentiate between flexible and non-flexible loads. These classification methods are designed to assist the HEMS in prioritising heat pump operation during low-cost periods, while deferring non-essential energy consumption.

Upcoming activities will involve exploring advanced machine learning models, such as XGBoost and LSTM networks, to refine demand forecasting capabilities. Efforts will also focus on improving model accuracy under variable seasonal conditions and enhancing the system's ability to predict HP load-shifting potential.

4.5.4.5 Design and Early-Stage Testing of Energy Market Pricing Prediction Models

The Wholesale Energy Market System (WEMS) is being developed to provide as much as possible accurate forecasts of electricity market prices, allowing consumers and aggregators to make informed decisions about load scheduling and demand response participation. The WEMS model has been trained on historical market data and incorporates multiple data categories, including grid-related information (such as solar, hydro and import/export data) and market-related metrics (such as buy/sell orders and DAM price trends).

Initial testing has demonstrated that the WEMS model, built using XGBoost, can achieve an approximate 85% accuracy in forecasting short-term Day-Ahead Market (DAM) prices. Additionally, real-time data ingestion pipelines have been established to continuously supply system and market operator data into the forecasting model, ensuring that the system remains responsive to dynamic market conditions. Future development will explore the integration of ensemble forecasting methods to improve prediction accuracy and enhance the system's ability to anticipate market volatility.

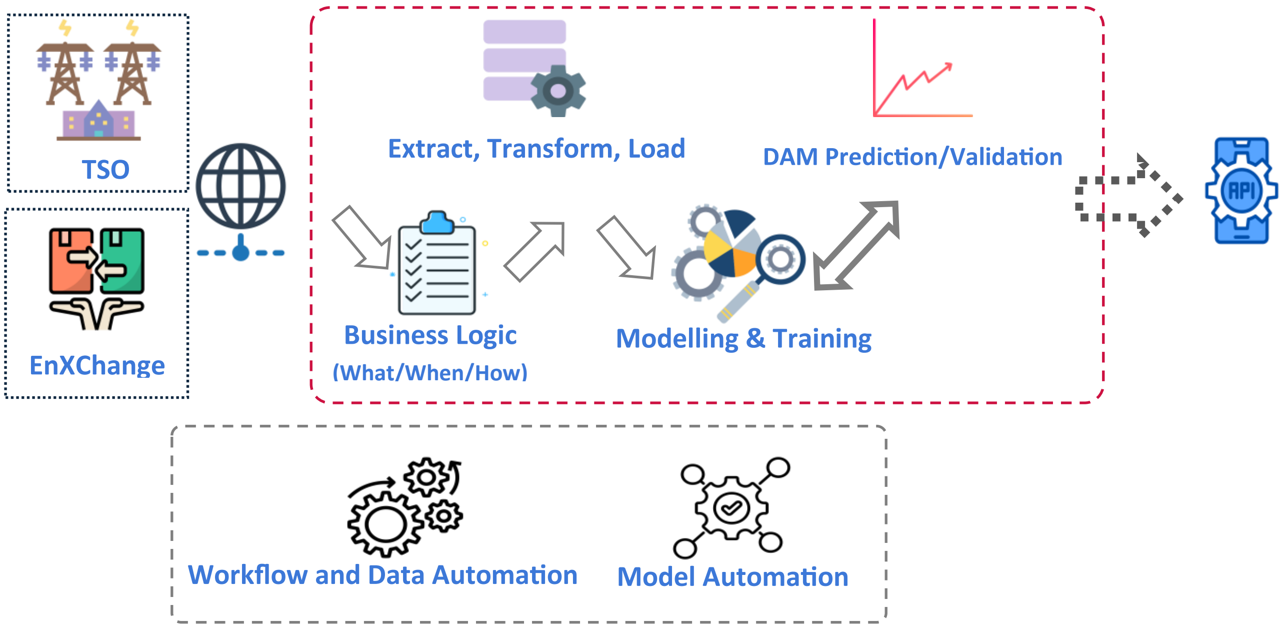

Figure 25 Concept of the model

4.5.4.6 Preliminary Investigation of DR Signal Transmission and Load Shifting Features

To ensure seamless integration of demand response mechanisms, efforts have been made to develop an effective DR signal transmission framework. The system is being designed to detect and respond to market signals, such as price fluctuations or grid congestion alerts, in real-time. Early investigations have resulted in a DR signal processing module that enables heat pumps to react dynamically to price changes. Preliminary designs of simulations are currently being scheduled to assess how load shifting affects consumer savings and peak demand reduction.

Moving forward, further development will focus on refining the system's ability to actively respond to near real-time DR signals in real-life market conditions. Efforts will also focus on creating an AI-driven adaptive control module capable of learning optimal load shifting strategies over time. Additionally, a dashboard interface will be developed to provide users with personalised recommendations, ensuring households can track their energy savings and assess the comfort impacts of DR strategies. With these ongoing improvements, the system is well-positioned to deliver cost savings, improve grid stability and enhance renewable energy utilisation in a decarbonised energy landscape.

4.5.5 Structural view and integration points

The architecture of the proposed framework is designed to be modular, scalable and interoperable, enabling the seamless integration of predictive power market modelling, automated DSM and heat pump control mechanisms. This section outlines the key components of the system, the initial interoperability layers that enable efficient data exchange and the aggregator/user interfaces that facilitate real-time decision-making.

4.5.5.1 General System Architecture

The system architecture consists of three core modules that form the backbone of asset monitoring, control and market interaction:

Home Energy Management System

- Monitors residential energy consumption and HP/PV system operation.
- Collects data from IoT sensors PV inverters and smart thermostats.
- Provides control signals to heat pumps based on market conditions.

Wholesale Power Market System

- Forecasts Day-Ahead Market (DAM) prices to identify optimal energy consumption periods.
- Utilises machine learning models (e.g., XGBoost) for price forecasting and predict market fluctuations.

Load-Shifting and Flexibility Impact Analysis

- Evaluates the economic impact of shifting HP loads to off-peak periods.
- Implements automated demand-side management mechanisms for grid-stabilising DR.
- Tracks user incentives and aggregated flexibility contributions via a dashboard interface.

These core modules operate autonomously yet interdependently, ensuring that HPs are dynamically controlled in response to market signals, renewable energy availability and user comfort preferences.

4.5.5.2 Interoperability Layers

Interoperability is key to the framework's functionality, as it involves multiple hardware and software components communicating seamlessly and securely. The initial architecture incorporates three primary interoperability layers:

1. IoT Data Exchange Format (HEMS Layer)

IoT-enabled HP controllers, PV inverters API and smart sensors send telemetry data via standardised protocols such as:

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- MQTT (Message Queuing Telemetry Transport) for lightweight real-time messaging.
- Modbus for industrial-grade equipment integration [78].
- RESTful APIs for cloud-based system interactions.

Data is pre-processed and stored in a time-series database, enabling fast analytics and historical comparisons.

2. Energy Market Data Exchange (WPMS Layer)

The WPMS module retrieves real-time and historical energy market data using:

- REST API endpoints from Market Operators.
- Grid load and generation data via Transmission System Operators (TSOs).

The forecasted energy prices are then fed back into the HEMS, guiding HP load scheduling decisions.

3. Predictive Model Integration (Flexibility Impact Analysis Layer)

The flexibility module integrates market prices, load-shifting scenarios and user comfort data to quantify economic benefits. It utilises automated decision-making algorithms, which trigger load-shifting if savings exceed predefined user thresholds. Data is exposed through graphical dashboards, ensuring transparency and user engagement. The interoperability layers ensure real-time data flow across multiple modules, enabling efficient load scheduling, demand response participation and user incentive tracking.

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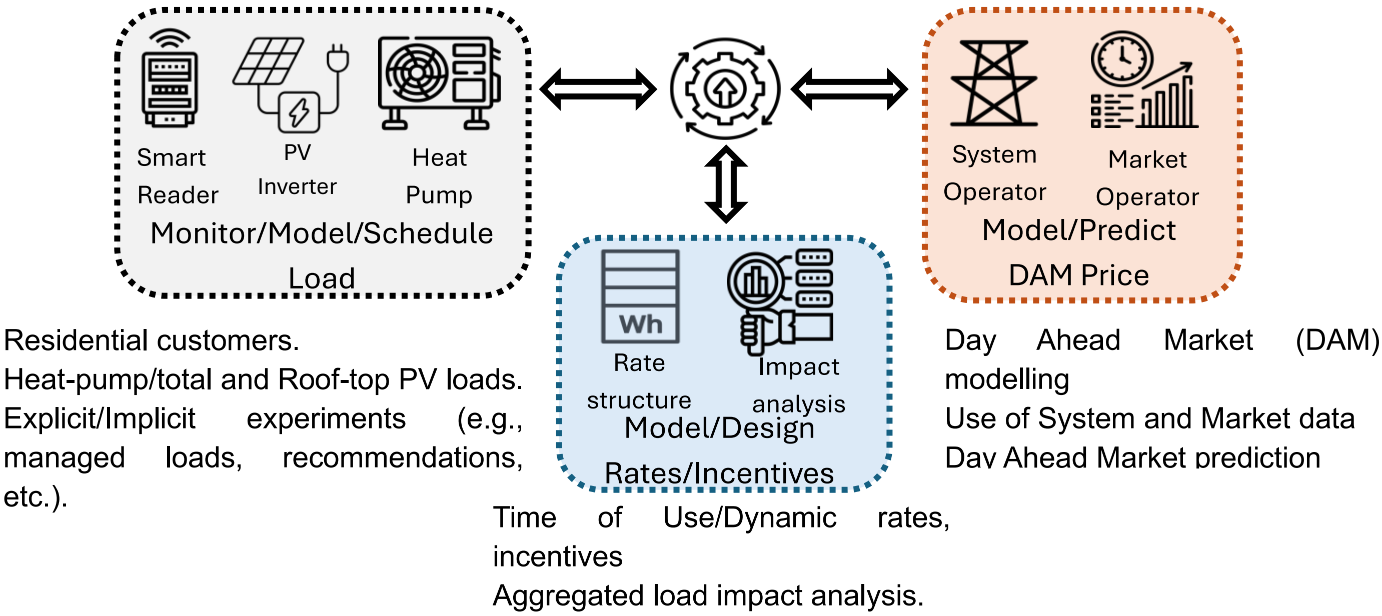

Figure 26 Interoperability layers

4.5.6 Interoperability considerations and preliminary findings

Ensuring seamless interoperability across the various modules of the proposed DSM and predictive energy market forecasting framework is critical to achieving a scalable, secure and efficient integration of home energy assets, energy markets and DR mechanisms. This section explores the preliminary data models, integration mechanisms, interoperability challenges and privacy measures necessary for a robust and adaptable solution.

4.5.6.1 Foreseen Data Models of Major Components

To support near real-time decision-making, predictive analytics and automated control, the solution relies on three primary data models:

Home Energy Management System indicative Data Model

- Captures near real-time energy consumption, heating demand and environmental conditions from IoT devices.
- Stores historical energy profiles to predict future demand and enable personalised energy-saving recommendations.
- Includes flexibility parameters (e.g., max allowable temperature drift, comfort thresholds, etc.).

Key attributes:

- Energy Consumption (kWh): At least 15-minute resolution for HPs, household appliances and PV inverters.
- Temperature Data (°C): Indoor/outdoor readings, heat pump flow temperatures and setpoints.
- Load Profiles: Distinguishing between flexible and non-flexible loads.

Wholesale Power Market System indicative Data Model

- Stores Day-Ahead Market (DAM) price forecasts, historical market trends and grid forecasted variables.

- Captures energy flow data and cross-border energy imports/exports.

Key attributes:

- Market Prices (€/MWh): DAM forecasts at hourly granularity.
- Grid Forecasts (MW): Predicted national demand and renewable energy supply.
- Interconnectivity Data (MW imports/exports): Market impact from neighboring energy exchanges.

Flexibility Impact Analysis Data Model

- Quantifies economic and grid stability benefits of demand-side flexibility.
- Tracks load-shifted energy volumes and their impact on cost savings and DR incentives.

Key attributes:

- Energy Shifted (kWh): Load shifted away from peak periods.
- User Incentives (€): Savings from demand response participation.
- Comfort Trade-offs (Δ°C): Ensuring compliance with user-defined comfort thresholds.

These three interconnected data models form the foundation of the solution, enabling intelligent coordination between household energy assets, predictive market modelling and demand response execution.

4.5.6.2 Initial Integration Mechanisms

Achieving scalable and flexible data exchange between components requires well-defined integration mechanisms. The solution employs a layered approach to communication, ensuring that market forecasts, load control signals and real-time IoT telemetry are aligned seamlessly. Some initial data handling tools and communication protocols are the following:

IoT Communication (HEMS Layer)

- MQTT (Message Queuing Telemetry Transport): Lightweight protocol for real-time sensor data streaming.
- Modbus: Industry-standard protocols for HPs, PV inverters and energy meters.
- Zigbee/Z-Wave [95]: Wireless communication for smart thermostats and load controllers.

Energy Market Data Exchange (WPMS Layer)

- RESTful APIs: Secure retrieval of market prices, grid conditions and renewable forecasts from external market operators.
- Streaming Data Pipelines: Handles market data ingestion.

Predictive Model & Flexibility Analytics Integration

- Database Storage: PostgreSQL for structured market data and time-series energy consumption data.
- Machine Learning Frameworks: XGBoost and TensorFlow [96] for price forecasting and load optimisation.
- Data Interoperability Layer: JSON and standardised RESTful API endpoints for exchanging model outputs between HEMS and WPMS.

4.5.6.3 Ensuring User Privacy and Data Security

Given that the proposed framework will process sensitive energy consumption data, ensuring robust data privacy and security protocols is paramount. The system has been designed to comply with General Data

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Protection Regulation (GDPR) requirements, while implementing technical measures that enhance data protection at every stage of the data handling process. This approach leverages consent mechanisms, data anonymisation, edge computing and regular security audits to safeguard user information and ensure responsible data management.

Central to the framework's privacy strategy is the use of explicit user consent mechanisms. Since the system actively controls heat pump operation based on market signals, maintaining transparency and user autonomy is essential. To achieve this, the framework adopts an opt-in model for demand response participation. Users are required to actively approve the system's ability to adjust heat pump settings before any automated control strategies are enabled. This consent model empowers users to make informed decisions about their involvement in load-shifting activities and provides the ability to define comfort preferences, temperature thresholds, or operating limits. By ensuring that all automated heat pump interventions require clear and informed consent, the framework not only aligns with GDPR principles but also builds consumer trust — a critical factor in encouraging widespread adoption

To further protect user privacy, the framework incorporates data anonymisation techniques that ensure personal information is never exposed or misused. As energy consumption data is collected, all user identifiers are replaced with hashed pseudonyms, rendering the data untraceable to specific individuals. In addition to pseudonymisation, the system should employ data aggregation methods to obscure individual consumption patterns. Rather than analysing individual household profiles in isolation, consumption data is combined with neighbouring households or broader energy clusters, ensuring that no specific user's behaviour can be identified.

This dual-layer approach — combining pseudonymisation with data aggregation — enhances privacy without compromising the system's ability to analyse energy trends and predict load-shifting opportunities.

The framework includes regular security audits recognising that cybersecurity threats are continually evolving. These audits are designed to proactively identify potential vulnerabilities in data pipelines that transmit heat pump telemetry, PV generation data and market forecasts, API endpoints responsible for connecting HEMS, WPMS and external data sources, as well as cloud storage systems that manage aggregated data and predictive analytics outputs.

4.5.6.4 Interoperability Challenges

While the proposed framework can offer a scalable integration structure, achieving seamless interoperability across various components presents several challenges. The complexity arises from the diversity of connected devices, the dynamic nature of energy market data and the need to balance automation with individual user comfort. Overcoming these obstacles is crucial for ensuring efficient heat pump control, effective DSM and accurate predictive modelling.

Heat pumps, PV inverters and thermostats often utilise distinct communication protocols, creating inconsistencies in data formatting, timing and control logic. This heterogeneity complicates seamless integration, particularly when different manufacturers rely on proprietary standards. To address this, the framework exploring generic IoT communication protocols and open API standards to create a common communication layer that allows diverse devices to exchange data efficiently.

Another key challenge relates to the latency of market data and the synchronisation of dynamic price forecasts. Electricity markets can be highly volatile, with price fluctuations occurring rapidly, often within short time intervals. To ensure heat pump load shifting strategies remain effective, the system must receive and respond to price updates with minimal delay. To mitigate this, the framework explores event-driven and REST-

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full services that utilise APIs. By incorporating low-latency data pipelines, the framework can ensure fast response times, improving both energy savings and grid reliability.

Furthermore, balancing dynamic load control with consumer comfort preferences presents yet another interoperability challenge. Each household has unique heating preferences and characterises such as building insulation, occupancy patterns and individual comfort expectations can vary. To address this, the framework explores adaptive comfort models that tailor heat pump schedules to individual household profiles. By dynamically adjusting heating profiles, the system ensures that load reductions do not compromise tenant comfort.

Finally, the framework should incorporate user feedback loops to refine personalised DSM strategies over time. By continuously gathering data on user satisfaction, temperature preferences and cost outcomes, the system progressively improves its ability to align automated load control with residents' specific comfort requirements. This learning-based approach ensures that consumers remain actively engaged, fostering greater trust in automated demand response systems.

4.6 Proactive maintenance services

4.6.1 Overview

The overall context for the development of proactive maintenance services within META BUILD project is the aim to ensure safe energy system operation for electrified buildings, guaranteeing service continuity and reducing maintenance-related operational costs.

To this aim, a predictive maintenance tool will be developed, following a classical Reliability Centred Maintenance (RCM) approach and Failure Mode Effects and Criticality Analysis (FMECA). In this way, fault scenarios will be identified for the technologies involved in the pilots addressed (Croatia and Spain). These technologies will be 1) energy storage batteries, 2) heat pumps and 3) PVTs. Effective fault prediction algorithms will be selected for the detection of each relevant fault. RCM will be used to design a suitable maintenance plan, according to the criticality of the faults and the available resources.

These algorithms will be selected from the analysis of relevant Machine Learning (ML) data-driven methods and model-based diagnosis. Then, they will be combined to constitute the so-called predictive maintenance tool. Depending on data availability (both from theoretical models and from monitoring), an incremental learning mechanism will be set up and integrated to improve detection reliability over time, especially in cases of data unbalance. Specific AI-based tools, such as one-class classifiers, will be employed.

4.6.2 Starting status, description and constraints

4.6.2.1 Introduction

The proactive maintenance services will be developed for technologies to be installed in the Croatian and Spanish demo sites.

The addressed technologies, present in both demo sites, are:

Croatia

- TE-2 District -heating-connected HPs.

Spain

- TE-6: Dual source Heat pump (DSHP)
- TE-7 PVTs with direct lamination aluminium absorber crystalline silicon unglazed collector
- TE-8 Air based PVTs

Further to that, TE-9 Second life batteries are being analysed as well.

Next, a description of common failures, often present for these technologies, is provided.

4.6.2.2 Heat Pumps

4.6.2.2.1 Introduction

Heat pumps are devices that transfer heat from one place to another using a refrigeration cycle. They can provide both heating and cooling, depending on the direction in which they operate. The primary components of a heat pump are the compressor, condenser, expansion valve, and evaporator.

4.6.2.2.2 Common faults

Heat pump technology provides an efficient and sustainable solution for heating and cooling buildings, improving classical heating and cooling applications. In most installations, there is evidence that a lack of maintenance can lead to significant operational inefficiencies. A high percentage of installations in buildings present heat transfer degradation and would need major compressor repair. Moreover, field surveys indicate significant losses in the heat pumps performance, with 20–50% of them operating at 70–80% efficiency or lower than their design efficiency, with faulty operation contributing an additional 40% of energy consumption. The loss of heat pump efficiency means significant energy losses and maintenance costs. Likewise, degraded efficiency leads to higher peak demand levels in periods of high energy usage.

Common Failures of heat pumps include:

1. Refrigerant Leaks

- **Symptoms:** Reduced heating or cooling performance, ice buildup on the evaporator coil.
- **Causes:** Corrosion, mechanical damage, poor installation, or manufacturing defects in the refrigerant lines or components.
- **Impact:** Reduced efficiency, potential damage to the compressor, and environmental concerns due to refrigerant release.

2. Compressor Issues

- **Symptoms:** Loud noises, reduced heating or cooling, frequent cycling on and off.
- **Causes:** Electrical issues, refrigerant problems, overheating, or wear and tear over time.
- **Impact:** Complete system failure if the compressor stops working.

3. Electrical Problems

- **Symptoms:** System not turning on, tripped circuit breakers, burnt wires or connectors.
- **Causes:** Faulty wiring, capacitor failures, thermostat issues, or problems with the control board.
- **Impact:** Loss of system functionality, potential safety hazards.

4. Thermostat Failures

- **Symptoms:** Incorrect temperature readings, system not responding to settings, continuous running or frequent cycling.
- **Causes:** Calibration issues, sensor failures, or electrical problems.

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- **Impact:** Inconsistent or incorrect heating and cooling, increased energy consumption.

5. Fan Motor Issues

- **Symptoms:** No air circulation, unexpected noise, or reduced airflow.
- **Causes:** Motor wear and tear, electrical problems, or issues with the fan blades or bearings.
- **Impact:** Reduced efficiency and comfort, potential system overheating.

6. Clogged or Dirty Filters

- **Symptoms:** Reduced airflow, increased energy consumption, decreased heating or cooling performance.
- **Causes:** Lack of regular maintenance and cleaning.
- **Impact:** Reduced system efficiency, potential for overheating and damage to other components.

4.6.2.3 Thermal Photovoltaics

4.6.2.3.1 Introduction

Photovoltaic thermal collectors are power generation technologies that convert solar radiation into usable thermal and electrical energy. PVT collectors combine photovoltaic solar cells (often arranged in solar panels), which convert sunlight into electricity, with a solar thermal collector, which transfers the otherwise unused waste heat from the PV module to a heat transfer fluid. By combining electricity and heat generation within the same component, these technologies can reach a higher overall efficiency than solar PV or solar thermal alone.

4.6.2.3.2 Common faults

Common faults in PVT systems prevent them from achieving their nominal power output and attaining the required level of energy production.

They can be classified in the following categories:

1. Electrical Failures

- **PV Cell Degradation:** Over time, PV cells can degrade, leading to reduced electrical output. Causes include exposure to ultraviolet (UV) radiation, thermal cycling, and mechanical stress.
- **Hot Spots:** Poor connections, shading, or cell defects can create hot spots, leading to local overheating and potential damage to the PV cells.
- **Inverter Failures:** Inverters, which convert DC to AC power, can fail due to component wear, thermal stress, or electrical surges.
- **Wiring Issues:** Loose or corroded electrical connections can cause power loss or electrical hazards.

2. Thermal System Failures

- **Leakage:** Leaks in the thermal collector, piping, or connections can lead to loss of heat transfer fluid, reducing system efficiency and causing potential damage.
- **Corrosion:** Corrosion of metal components, especially in liquid-based systems, can lead to leaks and system failures.
- **Scaling and Fouling:** Accumulation of mineral deposits (scaling) or debris (fouling) in the thermal collector or piping can reduce heat transfer efficiency.
- **Pump Failures:** Circulation pumps can fail due to mechanical wear, electrical issues, or blockages in the system.

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3. Temperature Control Issues

- **Overheating:** Insufficient cooling or poor heat dissipation can cause the PV cells to overheat, reducing their efficiency and potentially causing thermal damage.
- **Freezing:** In liquid-based systems, inadequate antifreeze protection can lead to freezing of the heat transfer fluid, causing pipe bursts and system damage.
- **Temperature Sensors:** Malfunctioning temperature sensors can lead to improper system operation, such as inadequate heating or cooling.

4. Mechanical Failures

- **Structural Damage:** Physical damage to the panels from weather events (e.g., hail, wind) or accidents can compromise the integrity and performance of the system.
- **Mounting Issues:** Improperly installed or weakened mounting systems can lead to panel misalignment, detachment, or reduced efficiency due to suboptimal orientation.

5. Control System Failures

- **Controller Malfunctions:** The system controller, which manages the operation of the PVT system, can fail due to software bugs, hardware issues, or power surges.
- **Communication Failures:** Loss of communication between system components can lead to improper operation or system shutdown.

4.6.2.4 Ion lithium batteries

4.6.2.4.1 Introduction

Second life battery storage systems operate in buildings by repurposing used batteries from electric vehicles (EVs) or other applications for energy storage. These batteries, which may no longer be suitable for their original high-performance uses, still have significant capacity for stationary energy storage applications.

4.6.2.4.2 Common faults

Second life battery storage systems, while cost-effective and sustainable, can face various challenges and failures due to their used nature and the complexities of integrating them into building energy systems. Some typical faults are presented next:

1. Capacity Degradation

- **Symptoms:** Reduced storage capacity and shorter discharge times.
- **Causes:** Aging of the battery cells, repeated charge-discharge cycles, and prior usage history.
- **Impact:** Lower overall efficiency and less energy available for use.

2. Thermal Management Issues

- **Symptoms:** Overheating, thermal runaway, or inconsistent temperature regulation.
- **Causes:** Inadequate cooling systems, poor heat dissipation design, or external environmental factors.
- **Impact:** Accelerated battery degradation, potential safety hazards, and reduced performance.

3. Battery Management System Failures

- **Symptoms:** Inaccurate State-of-Charge (SoC) readings, unbalanced cells, unexpected shutdowns.
- **Causes:** Faulty sensors, software bugs, poor integration, or hardware malfunctions.
- **Impact:** Reduced system efficiency, potential overcharging or deep discharging, and safety risks.

4. Electrical Failures

- **Symptoms:** Inconsistent power output, system interruptions, or complete system failure.
- **Causes:** Wiring issues, connector failures, inverter malfunctions, or electrical component wear and tear.
- **Impact:** Reduced reliability, potential damage to connected loads, and higher maintenance costs.

5. Cycle Life Reduction

- **Symptoms:** Shortened operational lifespan and frequent need for battery replacement.
- **Causes:** Intense cycling demands, improper charging protocols, or excessive discharge rates.
- **Impact:** Increased operational costs and decreased system reliability.

6. Cell Imbalance

- **Symptoms:** Uneven charge levels among cells, reduced overall capacity, and potential overcharging or undercharging of individual cells.
- **Causes:** Variations in cell aging, differences in cell capacity, or inadequate balancing by the BMS.
- **Impact:** Reduced efficiency, increased risk of cell damage, and potential safety hazards.

7. Corrosion and Chemical Degradation

- **Symptoms:** Visible rust, leakage, or swelling of battery cells.
- **Causes:** Exposure to moisture, poor sealing, or chemical reactions within aging cells.
- **Impact:** Potential safety hazards, environmental contamination, and reduced battery life.

4.6.3 Core technology aspects

4.6.3.1 Description of general framework and methodology: RCM and FMECA

4.6.3.1.1 Introduction

The traditional approach to maintenance, for many years, has been reactive. Reactive maintenance considers that equipment failure is bound to happen, so repairs are carried out when a machine stops functioning properly. Since downtime is almost certain, the objective is to get the equipment restarted as soon as possible through emergency repairs.

A proactive strategy refers to a systematic approach that focuses on preventing equipment failures before they occur. It emphasises actions designed to identify, monitor, and address potential issues at their root cause rather than reacting to problems as they arise.

The options for a proactive maintenance strategy include the following approaches, from the cheapest and simplest to implement, to the most advanced and complex:

- Preventive maintenance (PM): the most popular proactive maintenance strategy. Maintenance work is performed at regular intervals. The intervals are either calendar-based or usage-based.
- Condition-based maintenance (CBM): maintenance methodology where the condition of the asset is monitored through condition monitoring technology. Maintenance work is performed when sensors (or tests performed with handheld equipment) show that the asset is experiencing an issue.
- Predictive maintenance (PdM): uses a combination of condition monitoring sensors and machine learning to forecast when a machine is likely to fail. It works like an early warning system that gives

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maintenance personnel alerts, notifications, and enough time to plan and schedule repair/servicing before failure occurs.

- Prescriptive maintenance: goes one step beyond PdM. With prescriptive maintenance, the machines use sensors and analytics to perform self-diagnosis and present technicians with a few solutions on how to deal with the identified issue(s).
- Total productive maintenance (TPM): involves all stakeholders in the maintenance process, fostering a proactive culture. Operators play an active role by conducting routine maintenance tasks and inspections and contributing to continuous improvement efforts, leading to increased equipment effectiveness.

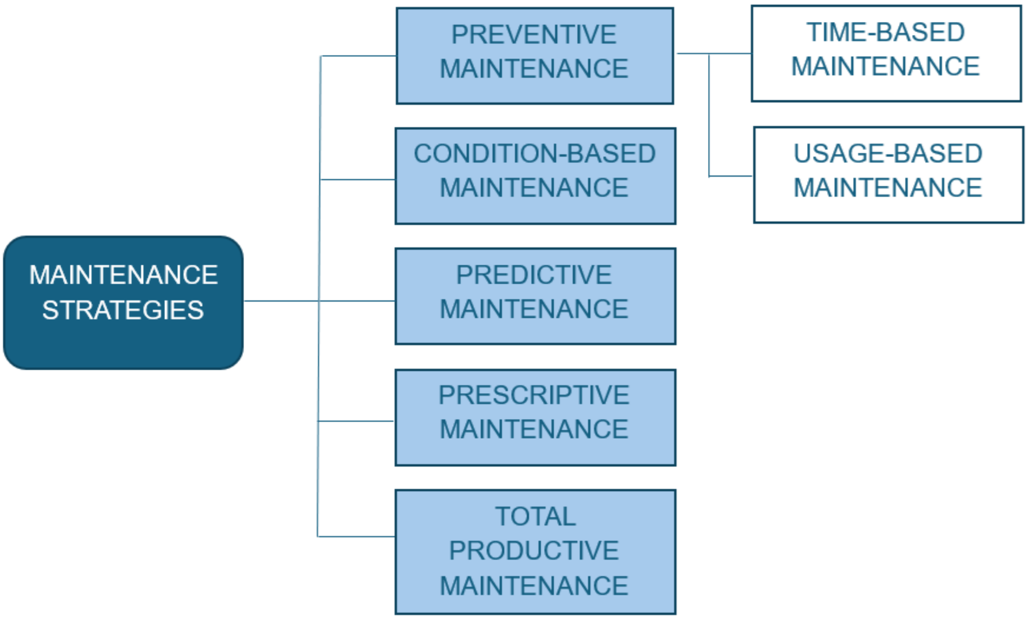

Figure 27 Maintenance strategies

Proactive strategies are designed to increase equipment reliability, optimise costs, minimise downtime, and extend the asset lifecycle, aligning closely with approaches like RCM and FMECA.

4.6.3.1.2 Reliability Centred Maintenance and Failure Mode, Effects, and Criticality Analysis

The proactive maintenance strategy to be developed and applied in META BUILD project will be based on the RCM and FMECA.

RCM is a structured methodology for optimizing maintenance strategies to enhance the reliability and performance of critical systems. It systematically assesses equipment and system functions, potential failure modes, and their impacts to identify the most effective maintenance tasks. The incorporation of FMECA ensures a thorough understanding of failure behaviours and their prioritisation. The RCM process is executed through the following seven steps:

- Step 1. System Selection: Ensure the selection criteria for the critical system include factors such as operational importance, safety implications, and the potential economic impact of failures. This initial prioritisation sets the foundation for later criticality assessments.
- Step 2. System Boundary Definition: While defining the system boundaries, identify the components or subsystems most critical to the system's operation. Highlight these areas for further detailed analysis in later steps.

- Step 3. System Description and Functional Block Diagram: Include an analysis of how each subsystem contributes to the overall functionality. Map out any interdependencies that could amplify the impact of failures in specific components, which will later inform the criticality assessment.
- Step 4. System Functions and Functional Failures: For each function identified, rank the functional failures by their potential to disrupt operations, safety, or environmental compliance. This preliminary ranking helps guide the focus of the criticality analysis in the subsequent steps.
- Step 5. Failure Modes, Effects and Criticality Analysis: Assess the failure modes, the severity, occurrence likelihood, the detection difficulty for each mode and integrate a criticality Analysis. Use a scoring system (e.g., Risk Priority Numbers, or RPN) or matrices to quantify the criticality of each failure mode, considering its potential consequences and likelihood.
- Step 6. Logic (Decision) Tree Analysis: Incorporate the results of the criticality assessment into the decision tree. Prioritise failure modes based on their criticality rankings, focusing on those with the highest potential impact to determine their importance and urgency. This ensures that the most critical issues are addressed first in the maintenance strategy.
- Step 7. Task Selection: Use the criticality data to tailor maintenance tasks to the specific needs of high-priority failure modes. For highly critical failure modes, assign predictive or preventive maintenance tasks, and for less critical modes, consider corrective or run-to-failure strategies if cost-effective.

These steps are described in some detail next:

Step 1. System Selection

The system components to be selected and included in the RCM methodology must be carefully identified. They should be critical in terms of derived operating costs in the event of failure. Repair costs and the consequences of loss of production during the maintenance shutdown should be considered.

In META BUILD project new technologies are being installed and tested in the different demos. In this sense, no historical failures or performance information is available. Therefore, decisions for system components selection will be based on the criteria and knowledge of the involved technical partners during the first stages of the equipment implementation.

The critical equipment will be identified within the overall system using a top-down notation as follows:

- Demo: either Croatia or Spain.
- System: set of elements that have a common function (e.g.: water storage, solar electricity production).
- Equipment: each of the energy generation, demand, storage, transport or transformation units (e.g.: PV panel, storage tank, heat pump).
- Element: each of the parts that make up a system (e.g.: pump, compressor, inverter).
- Component: The parts into which an item can be divided. Components are usually the parts replaced in a repair.

Criticality can be assessed by means of a set of parameters, related to equipment performance, maintenance cost and work planning and schedule:

<u>Equipment performance parameters</u>

The Reliability, Availability, and Maintainability (RAM) parameters are a way of measuring and assessing the performance of any equipment, being:

- **Reliability:** the ability to perform a specific function and may be given as design reliability or operational reliability.
- **Availability:** the ability to keep a functioning state in the given environment and using the defined processes.
- **Maintainability:** the ability to be timely and easily maintained (including servicing, inspection and check, repair and/or modification).

The metrics of RAM parameters are:

- Reliability is the probability that an equipment or system performs its function without failure during a specific time period, and can be measured as the Mean Time Between Failures (MTBF):

$$MTBF = \frac{T_{op,Tot}}{n_{fails}}$$

Where $T_{op,Tot}$ is the total operating time and n_{fails} is the number of failures in that period.

- Maintainability is the probability of performing a repair in a specific period of time, and can be measured as the Mean Time To Repair (MTTR):

$$MTTR = \frac{T_{down,Tot}}{n_{outages}}$$

Where $T_{down,Tot}$ is the total down time and $n_{outages}$ is the number of outages.

Availability (A) is the probability that an equipment or system is available for operation in a specific time period, and can be calculated as:

$$A = \frac{T_{op,Tot}}{T_{op,Tot} + T_{down,Tot}} = \frac{MTBF}{MTBF + MTTR}$$

These parameters can be characterised in terms of the parameters, mean or any percentile of a probabilistic distribution, in most cases, the exponential distribution one. The metrics will be initially calculated for every equipment in the demos and could be extended to individual components that are considered as critical.

Maintenance cost parameters:

Cost associated with maintenance tasks or due to a lack or poor maintenance should be considered.

Maintenance Cost / Equipment (MCE): expressed as the total economic cost assumed by a technology provider to perform maintenance tasks divided by the number of equipment installed in the demos:

$$MCE = \frac{k€\, maintenance\ tasks}{\#\ equipment}$$

- Maintenance Cost / kWh produced (MCU): expressed as the total k€ spent by a technology provider in maintenance tasks divided by the total amount of energy produced by their equipment:

$$MCU = \frac{k€\, maintenance\ tasks}{kWh\ produced}$$

Work planning and schedule parameters

These parameters are oriented to assess the performance of a preventive maintenance program and/or identifying opportunities to reduce reactive maintenance.

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Planned Maintenance Percentage (PMP): expressed as the percentage of total maintenance hours spent on planned maintenance tasks in a given period:

$$PMP = \frac{\#\,planned\ maintenance\ hours}{\#\,total\ maintenance\ hours} \cdot 100$$

Step 2. System Boundary Definition

Clear boundaries will be established for every system, which is made up of pieces of equipment. Since only the critical ones will be included for the analysis, there will be others, not so critical, but needed to establish the right boundaries. Systems will be considered as units for which inputs and outputs must be defined as previous step for the functional block diagram definition.

Step 3. System Description and Functional Block Diagram

All the functions of the system under study will be detailed and quantified whenever possible. Standards will be considered when appropriate (specification to be met by the system or limits of operation of the different variables).

For a system to perform its function, all the pieces of equipment inside it must meet theirs. The same applies to the elements and components. Functions will be specified at lower levels than system level whenever needed.

Each function will be normally documented as a statement containing a verb, an object and a performance standard. The performance standard describes the minimum acceptable requirement, rather than the design capability. It must be noted that after a failure, maintenance can only restore the asset to its initial design capability. Performance standards are used to define failures, and this is needed for the maintenance decision-making process.

Functions can be categorised as:

- Primary functions: the reasons why the system/equipment exists or has been acquired.
- Secondary functions: most systems/equipment will have secondary functions that will generally be less obvious than the primary functions, although their failure may sometimes have worse consequences. These are additional functions that augment the satisfaction of the user, for example safety, comfort, control, structural integrity, aesthetics and efficiency.

One method for identifying functions is to develop a functional block diagram of the system. A functional block diagram is a graphical representation of the system operation. It typically contains (1) the inputs (e.g., materials, energy sources) entering the system boundary, (2) the blocks representing the functions that occur within the system boundary, and (3) the outputs (e.g., materials, energy, signals) leaving the boundary. In addition, arrows are used to depict the flow of materials, energy, signals, etc., between functional blocks and into and out of the system. Within the boundary, each block represents a primary or secondary function that must be provided for the system to convert the inputs into outputs.

Step 4. System Functions and Functional Failures

A functional failure is defined as the unfitness of any assets to perform a function to the expected and acceptable performance standards set by the user. At this stage, the objective is to identify which are the circumstances under which we can declared a faulty state. There are four different aspects of functional failures to be considered:

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- The complete loss of function is known as total failure; whereas if the asset functions but performs outside acceptable limits it is known as partial failure.
- Going over the upper and/or lower limit of the performance standards: An asset will be considered to be in a failed status if one or more values of the output signals are over the upper and/or under the lower limit.
- There are functional failures associated with the performance standards.
- The operating context of the asset: The failed state may be different for identical assets, depending upon the operating context.

Step 5. Failure Modes, Effects and Criticality Analysis

At this step, the purpose is to establish the cause-and-effect relationship between potential equipment failures and the end effect of the functional failures, as well as to evaluate the criticality of the related failure mode. There are a number of published guidelines and standards for the requirements and recommended reporting format of FMEAS and FMECAs. Some of the main published standards for this type of analysis include SAE J1739, AIAG FMEA-4 and MIL-STD-1629A, and many industries and companies have developed their own procedures to meet the specific requirements of their products/processes. In META BUILD project we are proposing a particular FMECA adapted to the available systems in Croatia and Spain demos.

In conducting the FMECA, there are two basic sub-steps:

- Identifying the failure mode and its effects.
- Assessing the criticality of the failure mode.
- For the first step, a top-down approach will be followed, by analysing each function and its associated functional failures. This approach focuses on determining what effects different functional failures have on the operation of the system and then what equipment failures (i.e., failure mode) can result in the functional failure.

Failure modes can be classified in three groups, as shown below:

- Falling capabilities:
  - Lubrication failures.
  - Dirt.
  - Human errors.
  - Disassembly.
  - Deterioration.
- Increase in desired performance:
  - Sustained deliberate overloading.
  - Sustained unintentional overloading.
  - Sudden unintentional overloading.
  - Incorrect process material
- Initial incapability.

Understanding the factors that can have an influence on equipment failures is also interesting. Some of the most common ones are the design error, faulty material, improper fabrication or construction, improper operation, inadequate maintenance, maintenance errors.

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Once the failure modes have been identified, the next step is to describe and list what happens when a failure mode occurs. These are known as failure effects. Equipment failures may affect safety, operations, and other equipment. Identifying the consequences of failures and evaluating them helps in the proactive maintenance decision making process.

Failure effects can be divided into four groups:

- Hidden Failure Consequences: Hidden failures have no direct effect but expose the whole system to multiple failures with serious, often catastrophic, consequences. Most of these failures are associated with protection devices that are not fail-safe.
- Safety and environmental impact: A failure has safety consequences if it could injure or kill someone. It has environmental consequences if it could lead to a breach of any corporate, regional, national or international environmental standard.
- Operational consequences: A failure has operational consequences if it affects the production and/or performance of the system (output, product quality, customer service or operating costs in addition to the direct cost of repair). In the META BUILD project, these failures are related to user comfort and energy savings.
- Non-operational consequences: Obvious failures that fall into this category do not affect safety or production, so they only involve the direct cost of repair.

An Asset Criticality Analysis (ACA) is used to assess criticality. This is a methodology by which assets are assigned a criticality rating based on their potential risk and enables an understanding of how relevant each asset is to achieve the economic and non-economic objectives of the overall system being analysed. Performing a criticality analysis also helps to clarify what can be done to reduce the risk associated with each asset. The ACA methodology will include a qualitative criticality analysis and a Risk Priority Number (RPN). The RPN will be a measure of the criticality of each failure mode. The RPN will take into account three different aspects of the failure:

- Severity (SEV): a qualitative measure of the potential impact of each failure mode
- Occurrence (OCC): qualitative measure of the likelihood of each potential failure mode occurring
- Detection (DET): a qualitative measure of the likelihood of prior detection of each potential failure mode.

Each of these aspects can be rated in a scale from 1 to 6 according to the next definitions:

Table 3 Severity scale for Risk Priority Number

Severity	Definition
1	None effect on safety, health, environment or function
2	Minor disruption to facility function and repairing doesn’t affect the mission
3	Minor disruption to facility function and long time in restoring the function affecting the mission
4	Moderate disruption to facility function and moderate time in restoring the function
5	High disruption to facility function. All mission is lost and significant delay in restoring the function
6	Potential safety, health or environmental issue

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Table 4 Occurrence scale for Risk Priority Number

Occurrence	Definition
1	Remote probability of occurrence
2	Low failure rate
3	Occasional failure rate
4	Moderate failure rate
5	High failure rate
6	Very high failure rate

Table 5 Detection scale for Risk Priority Number

Detection	Definition
1	Very high probability of prior detection
2	High probability of prior detection
3	Moderate probability of prior detection
4	Low probability of prior detection
5	Very low probability of prior detection
6	No possibility of prior detection with the existing detection methods

Using this qualitative rating of the different aspects, the RPN will be defined as:

$$RPN = SEV \cdot OCC \cdot DET$$

Once the RPN has been calculated for each failure mode, it is possible to classify the failures according to their criticality. This classification and cost assessment will be used to decide the type and priority of maintenance actions.

The RPN will not be a static value over the life cycle of the equipment or systems. During the initial approach to FMECA, the severity, occurrence and detection values will be set using the previous knowledge and experience of the technology providers.

As long as measurements and KPIs of the system operation are available, actual data could be used to recalculate the RPNs. Also, the proactive maintenance methodology itself will be the source of changes to the RPNs, as newly implemented maintenance and detection strategies will change the detection value.

Step 6. Logic (Decision) Tree Analysis

The purpose of building a Logic Tree Analysis is to have a visual tool that helps to assign priorities to the failure modes.

Once the failure modes have been listed for each component of the system and the functional dependence among all failure modes of components and functional failures has been found, it is necessary to establish the influence of each failure mode at the local level, as well as at the levels of system and plant. Such decisions are not at all simple, so the logic tree shown next is used for that purpose. Classification of the effects of failure modes according to the logic tree analysis puts every failure mode in one of the following 4 groups:

- A: safety problem.
- B: outage problem.
- C: minor (insignificant) economic problem.
- D: hidden failure.

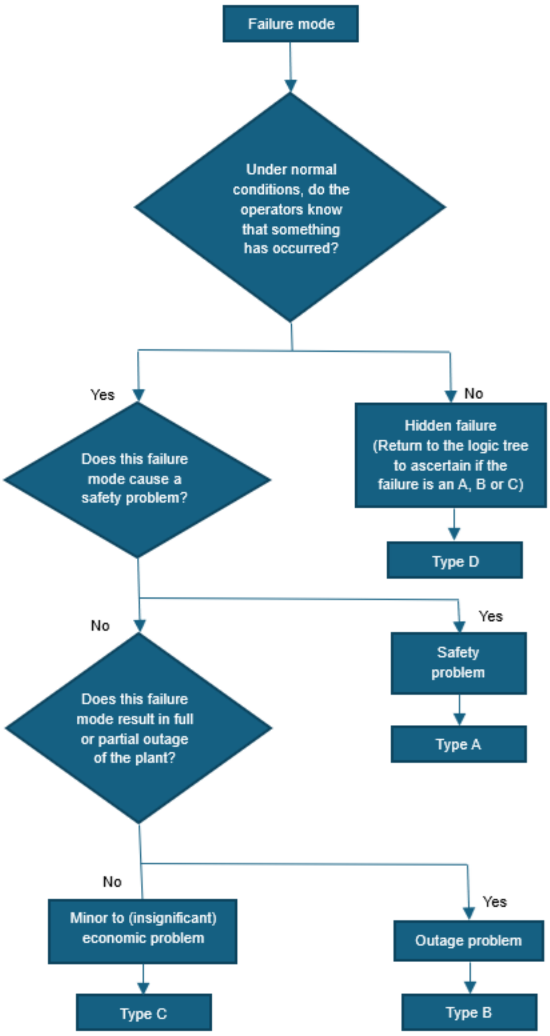

Figure 28 Failure mode logic tree (based on (Petrovic, Car, Radicevic, Sikulec, & Grkovic, 2014))

Step 7. Task Selection

The objective of this last step is to select the most appropriate maintenance strategy for each failure mode in order to predict or prevent the failure. In addition, since the RCM methodology is designed to continuously review the maintenance strategy, an iterative process is implemented based on new information about the system operation.

In this step it is necessary to assign a maintenance activity to each failure mode. This activity should prevent the occurrence of the failure mode in the most efficient way or provide maximum reduction of its effect. Each selected type of activity should have its description and details of its periodic repetition. The decision tree in next Figure 29 can help with this.

The type of maintenance task will use the following definitions:

- Run-to-failure: when it is not possible to anticipate the failure mode and corrective actions are performed.
- Preventive: includes scheduled recovery tasks and scheduled retirement tasks.
- Condition-based: includes all maintenance tasks triggered by a monitored index or value. These values may be calculated by methods such as condition monitoring and/or predictive algorithms.

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- Redesign: includes all tasks that implement a new design in the hardware (equipment/components), monitoring system, detection tools or specified operating procedures.

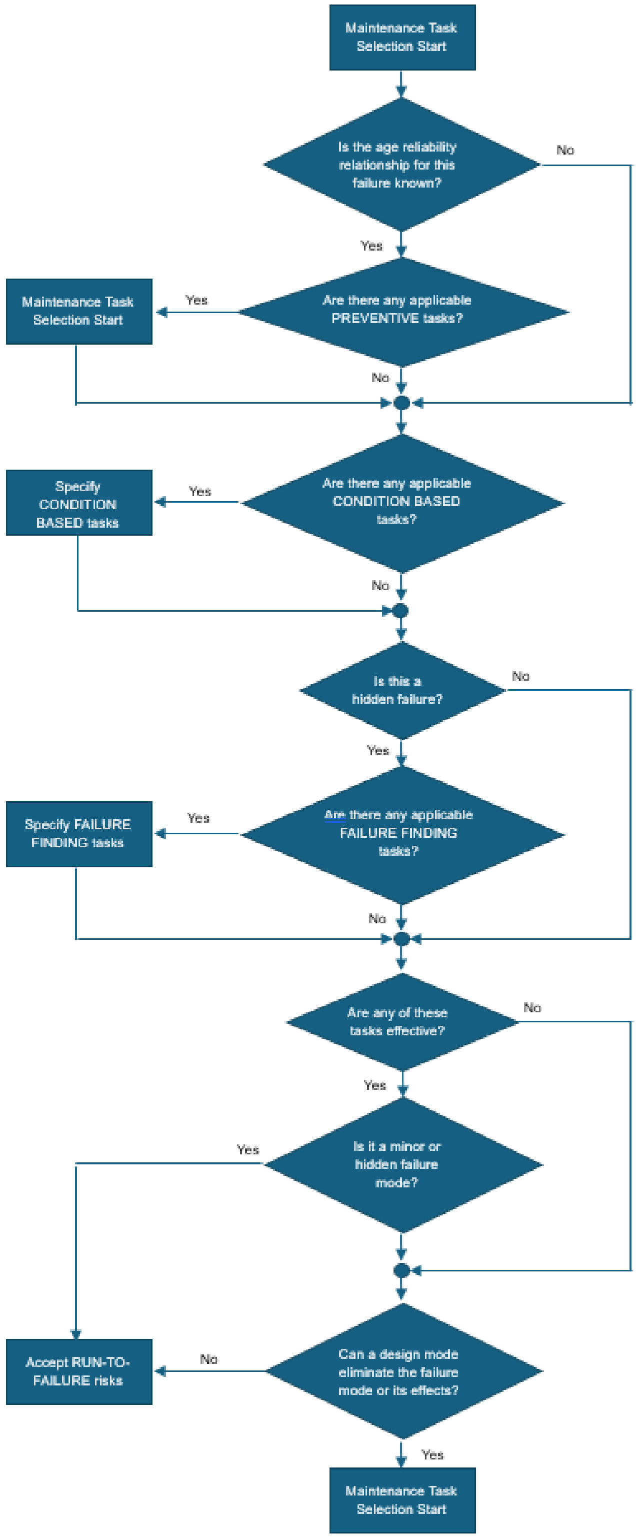

Figure 29 Decision tree for maintenance-tasks selection (based on (Petrovic, Car, Radicevic, Sikulec, & Grkovic, 2014))

4.6.3.2 Review of ML and model-based algorithms for fault prediction

A system is considered to be operating normally when it performs its intended functions without faults. A fault is an unpermitted deviation of at least one system parameter or characteristic from acceptable conditions

[17]. If unresolved, a fault can lead to failure, which is the permanent loss of the system's ability to perform its required function.

There are two main approaches that can be normally followed to perform fault detection and diagnosis (FDD) in a plant or industrial system. These are: the ML or data-driven, and the model-based approaches.

Model-based monitoring methods compare process measurements with predictions from a mathematical model, typically derived under fault-free conditions using fundamental process knowledge. The residuals—differences between measured and predicted values—serve as indicators of faults [18], [19]. Under normal operation, residuals remain near zero, accounting for modelling uncertainties and measurement noise. When a fault occurs, significant deviations from zero signal an abnormal condition.

These approaches include observer-based methods [20], [21], parity space techniques [22], [23], [24], [25], and interval-based methods [26]. The effectiveness of model-based monitoring depends on the accuracy of the underlying models.

Data-driven monitoring methods rely on historical data from a fault-free process [27] to build empirical models for fault detection. These models analyse new data to identify deviations from normal operation. Common approaches include latent variable regression techniques such as partial least squares (PLS) regression, principal component analysis (PCA), independent component analysis (ICA), and canonical variate analysis (CVA) [28], [29]. Other methods include neural networks [30], fuzzy systems [31], pattern recognition [32], and support vector machines (SVM) [33], [34]. SVM-based techniques are particularly useful for nonlinear systems, offering advantages over traditional nonlinear optimisation methods.

4.6.4 Technology progress and status

At this stage of the project, the degree of available detail for some of the technologies from WP3 – "Technologies enabling electrification" is limited and there are no models which are accurate enough to provide the theoretical values needed in typical fault detection algorithms.

As a starting point, less detailed models for the technologies are going to be assumed, and a number of methodologies are proposed for the detection of common faults in heat pumps and batteries.

4.6.4.1 Fault detection for heat pumps

The Coefficient of Performance (COP) serves as indicator for the most critical faults in heat pumps. A method has been devised to detect poor performance, linked to faulty states, through the calculation of the COP.

The COP of a HP is defined as the ratio between the heating capacity and the electric consumption. The COP of a certain machine depends on the operating point in terms of mass flow and inlet and outlet temperatures at condenser and evaporator. Since COP is usually specified by manufactures, it can be calculated online in order to decide whether the HP is working in a usual operating point, or it presents a faulty state. The data needed to evaluate the COP are condenser mass flow, inlet temperature and outlet temperature at condenser side of the HP and electricity consumed by its compressor.

The theoretical limit for the COP of a heat pump operating between source (evaporator) and sink (condensator) with constant temperatures is defined by the Carnot process, which is given by:

$$COP_{Car} = \frac{T_H}{T_H - T_L}$$

This equation shows that the Carnot efficiency depends on the condensation and evaporation temperatures. With an ideal compression cycle without losses, it would be possible to achieve the Carnot efficiency.

For a trans-critical heat pump this formula is not valid, because there is no condensation temperature, but a temperature range in the gas cooler. The theoretic maximum efficiency of a trans-critical heat pump is described by the Lorentz efficiency [35]. Based on the Second Law of Thermodynamics, the COP of a reversible HP operating between two finite reservoirs can be determined by the following expression:

$$COP_{Lorentz} = \frac{\overline{T}_H}{\overline{T}_H - \overline{T}_C}$$

Where $\overline{T}_H$ and $\overline{T}_C$ are the entropic mean temperatures of the heat sink (hot) and source (cold) sides respectively. The difference between them can be referred as mean temperature lift: $\Delta\overline{T}_{lift} = \Delta\overline{T}_H - \Delta\overline{T}_C$

This equation is similar to the previous one, based on Carnot, but now the constant temperatures can be substituted by the logarithmic mean temperature for the source and the sink, respectively, given by:

$$\overline{T}_H = \frac{\Delta T_H}{\ln\left(\frac{T_{H,o}}{T_{H,i}}\right)} \qquad \overline{T}_C = \frac{\Delta T_C}{\ln\left(\frac{T_{C,i}}{TC,o}\right)}$$

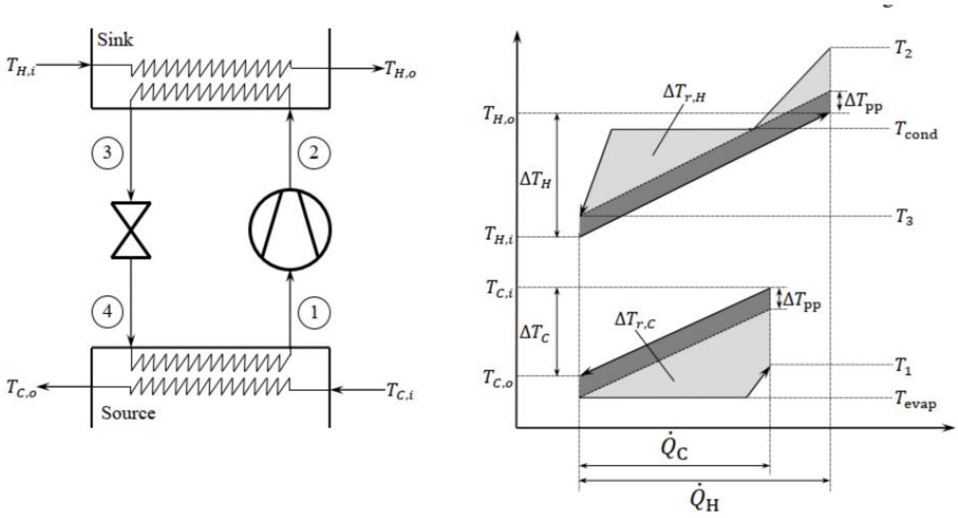

Figure 30 Cycle configuration of a simple one-stage heat pump process and schematic diagram of a temperature heat load.

Based on this concept, later developments were carried out. A possible generalised performance estimation method is presented by Jensen [36]. This method accounts for internal irreversibility associated with entropy generation during compression and expansion processes, as well as external irreversibility arising from finite temperature differences across heat exchangers and limitations in thermodynamic integration between the refrigerant and the heat source and sink. Thus, the expression proposed by Jensen et al. introduces real process parameters such as the compressor efficiency and heat loss, characteristics of heat exchangers and those related to the working fluid.

A possible performance estimation expression is formulated as:

$$COP = COP_{Lorentz} \cdot \frac{1 + \frac{\Delta\overline{T}_{r,H} + \Delta\overline{T}_{P,P}}{\Delta\overline{T}_H}}{1 + \frac{\Delta\overline{T}_{r,H} + \Delta\overline{T}_{r,C} + 2\Delta\overline{T}_{P,P}}{\Delta\overline{T}_{lift}}} \cdot \eta_{is,c} \cdot \left(1 - \frac{W_{is,e}}{W_{is,c}}\right) + 1 - \eta_{is,c} - f_Q$$

This expression takes into account the following terms:

- Sink and Source inlet and outlet temperatures, through the terms $\Delta\overline{T}_H$ and $\Delta\overline{T}_{lift}$.
- Compressor isentropic efficiency $\eta_{is,c}$, compressor heat loss ratio f_Q , and HX pinch point temperature difference $\Delta\overline{T}_{PP}$.
- Ratio between the isentropic work in the expansion and compression process $\frac{w_{is,e}}{w_{is,c}}$, refrigerant induced temperature difference $\Delta\overline{T}_{r,C}$ and $\Delta\overline{T}_{r,H}$.

In order to simplify the expression, applied some approximations to the heat exchanger pinch and the refrigerant induced temperature difference in the evaporator resulting in a good approximation for azeotropic refrigerants with moderate superheating and a constant capacity source:

$$\Delta\overline{T}_{PP} \approx \Delta T_{PP} \quad \Delta\overline{T}_{r,C} \approx \frac{1}{2}\Delta T_C$$

Additionally, for $\frac{w_{is,e}}{w_{is,c}}$ and $\Delta\overline{T}_{r,H}$ a linear approximation was applied to fit these values for the refrigerants Ammonia and Isobutane based on a simulation model. The obtained coefficients are shown in Table 6.

$$\Delta\overline{T}_{r,H} = a \cdot \left(T_{H,o} - T_{C,o} + 2\Delta T_{PP}\right) + b \cdot \Delta T_{\sin k} + c \qquad \frac{w_{is,e}}{w_{is,c}} = a \cdot \left(T_{H,o} - T_{C,o} + 2\Delta T_{PP}\right) + b\Delta T_{\sin k} + c$$

Table 6 Coefficients for the linear models for $\Delta\overline{T}_{r,H}$ and $\frac{w_{is,e}}{w_{is,c}}$ both for ammonia and isobutane

Parameter	Ammonia			Isobutane		
	a	b	c	a	b	c
$\frac{w_{is,e}}{w_{is,c}}$	0,0014	-0,0015	0,039	0,0035	-0,0033	0,053
$\Delta\overline{T}_{r,H}$	0,20	0,20	0,015	-0,0011	0,30	2,4

Jensen COP is proposed as a good approximation of the real COP and will be used as indicator to detect potential faults in HPs.

4.6.4.2 Fault detection for batteries

The final batteries that will be installed in the demo sites are not yet available. However, some data from tests performed on similar ones has been made available for some preliminary analysis.

These tests consisted of charging and discharging cycles, as well as obtaining Electrochemical Impedance Spectroscopy (EIS) data for 15 Panasonic NCR18650BD cells. More specifically, series of 50 cycles starting from 0 and ending in 300 were performed to the battery cells.

The kinds of tests were:

- CCCV Chg: When the battery voltage is below a set voltage value, the testing device charges the cell battery in a constant current mode until the battery reaches the set constant voltage value and then enters a Constant Voltage process.
- CC DChg: Once the cell battery has been charged, it is discharged at constant current, and the voltage drops. The cut-off voltage and the constant current value are set to specific values.

Three sets of data were obtained and analysed. The key parameters in each set were:

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- Direct Current Internal Resistance (DCIR).
- Coulombic Efficiency.
- Electrochemical Impedance Spectroscopy.

4.6.4.2.1 Analysis of Direct Current Internal Resistance

DCIR is one of the important indexes to evaluate battery performance. The test of internal resistance includes AC internal resistance and DC internal resistance. For single-body cells, AC internal resistance is generally used to evaluate, which is often called ohmic internal resistance.

DCIR is obtained by applying a short pulse of high current to the cell. The voltages and currents are measured before and after the pulse and then ohm's law (I = V/R) is applied to get the result.

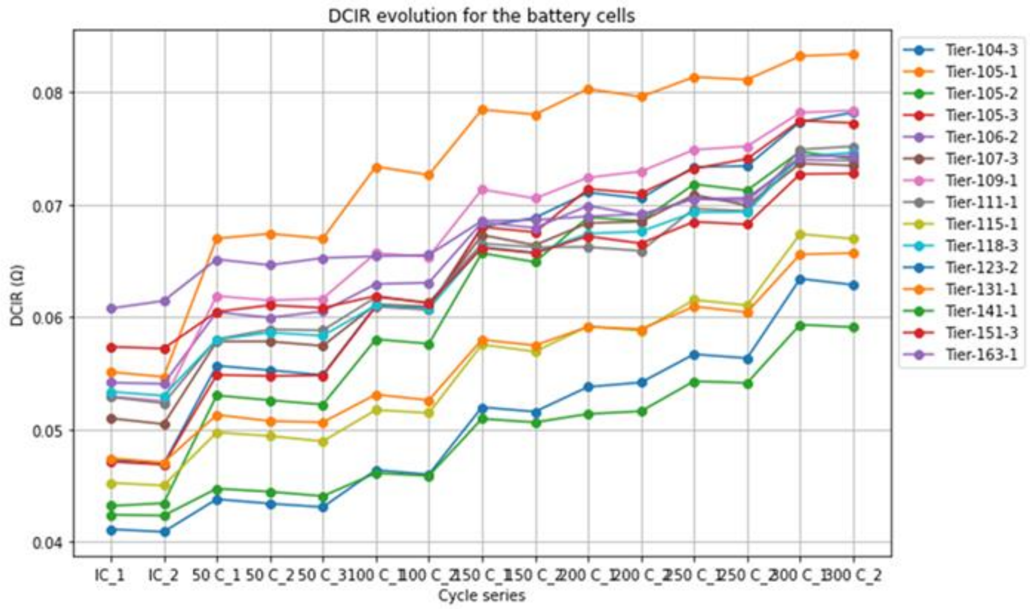

Figure 31 DCIR evolution for the battery cells

DCIR values can be used to estimate the health status of the batteries. In this regard, a healthy lithium-ion battery should show a gradual increase in DCIR over its lifetime. However, a steep increase in DCIR over a short number of cycles can indicate accelerated degradation. Typical new battery DCIR values range from 10 to 100 mΩ (depending on chemistry and design). A battery can be considered degraded when DCIR exceeds twice its initial value (e.g., from 50 mΩ to 100+ mΩ). If DCIR reaches above 200-300 mΩ, the battery is often classified as damaged.

Next, the DCIR values obtained along the 0 to 300 charging and discharging tests cycles are represented for the 15 battery cells.

4.6.4.2.2 Analysis of Coulombic Efficiency

Coulombic efficiency (CE) is the ratio of discharge capacity to charge capacity within the same cycle. Since the CE of lithium-ion batteries is very close to 100%, it is hard to measure it precisely. The relationship between CE and State of Health (SOH) has a great influence on battery performance.

- Ideal CE = 1 (100%): Indicates that there are no charge losses between the charge and discharge processes, which is theoretically impossible in real systems.
- CE in new batteries (~99.5% - 99.9%): In good quality lithium-ion batteries, the coulombic efficiency is usually very high, indicating low losses.

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- Low CE (<99%): May indicate inefficiencies due to parasitic reactions, formation of Solid Electrolyte Interphase (SEI), electrolyte degradation or loss of active lithium.
- Declining EC trend: As the battery ages, the CE may decrease due to degradation mechanisms such as lithium deposition, SEI growth or loss of active capacity.

Typical SOH thresholds:

- 80% SOH: Critical Threshold
    - This is the most common criterion for considering a battery to have reached the end of its useful life.
    - At this point, the usable capacity has decreased enough to affect performance.
    - Used in applications such as electric vehicles and stationary storage.
- 85% SOH: Warning Threshold
    - Used in some systems to indicate significant deterioration, although the battery is still functional.
    - Can be useful in predictive maintenance strategies.
- 70% SOH: Degraded battery.
    - Below this value, performance is often insufficient for many applications.
    - Sometimes allowed in less demanding applications before recycling.

Figure 32 shows the evolution of the Coulombic Efficiency against the State of Health for one of the cells.

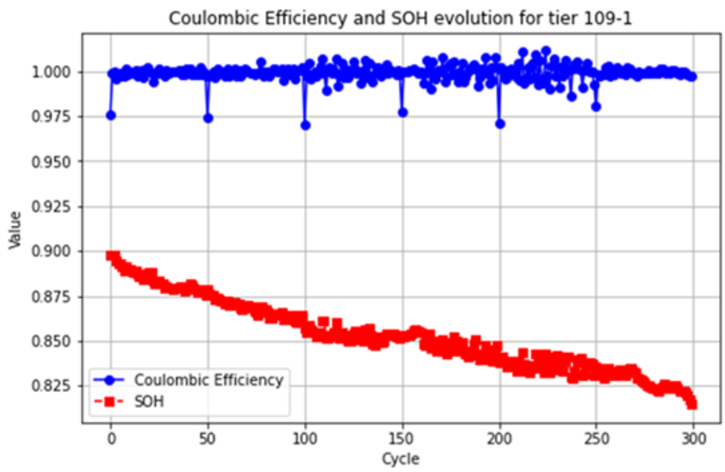

Figure 32 CE and SOH evolution along the 300 cycles for the battery cell "109-1"

4.6.4.2.3 Analysis of Electrochemical Impedance Spectroscopy

EIS can quickly and non-invasively measure the SoH of Li-ion batteries and help improve the performance of energy storage systems. EIS uses a Nyquist plot to represent an impedance spectrum's real and imaginary parts and provide insights into reaction mechanisms and battery SoH. It is based on the application of a low amplitude alternating current (AC) or voltage signal over a range of frequencies and measures the cell response in terms of impedance. Through the analysis at different frequencies (from mHz to kHz or MHz), information is obtained about different physical processes inside the cell, such as electrolyte resistance, charge transfer at the electrodes and diffusion of ionic species.

Interpretation in Lithium-Ion Batteries:

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1. High frequency (>1 kHz): Represents the resistance of the electrolyte and the contact resistance between the electrode materials.

2. Medium frequency (10 Hz - 1 kHz): Related to the charge transfer resistance, which depends on the electrode-electrolyte interface and is influenced by the health of the cell.

3. Low frequency (<10 Hz - mHz): Associated with ion diffusion processes within the electrodes (Warburg impedance), which is related to charge storage capacity and battery degradation.

Applications of EIS in Batteries:

- Degradation diagnosis: Allows identification of ageing mechanisms such as SEI layer growth, loss of active lithium or increased charge transfer resistance.
- SOH estimation: The evolution of parameters obtained from EIS spectra can be used to predict battery life.
- Equivalent circuit modelling: Models such as the Thevenin model or the Randles model are fitted to represent the electrochemical behaviour of the battery.

From the available data, a number of features have been calculated:

- Electrolyte resistance (reals@1): A value representative of the cell resistance at high frequencies.
- Charge transfer resistance (reals@9 - reals@1): This is the difference between the impedance at high and low frequencies, representing the resistance to charge transfer.
- Phase angle: arctan(imags@X / reals@X) for intermediate frequencies.
- Total impedance (impedance modulus): sqrt(reals@X^2 + imags@X^2) for each frequency.

Figure 33 shows these values for a specific battery cell:

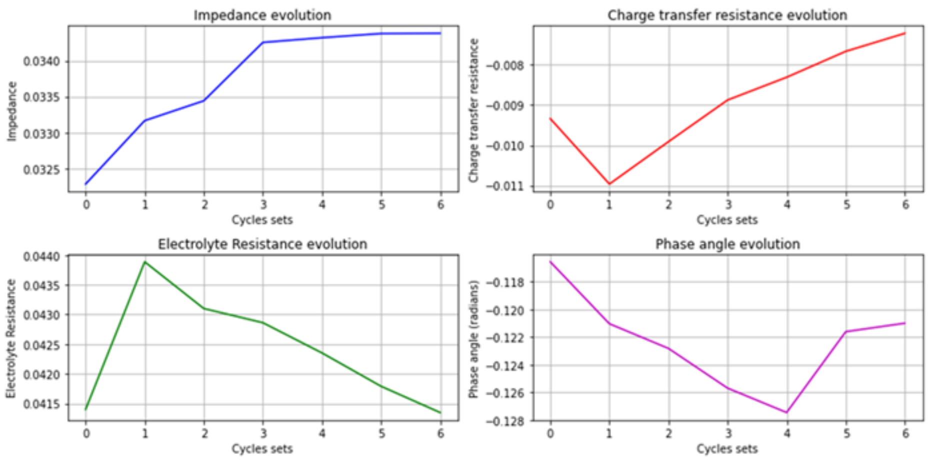

Figure 33 Evolution of different parameters extracted from EIS, along the 300 cycles for the battery cell "104-3"

4.6.5 Ongoing work

The ongoing work and the next development cycle for *TE-15 Proactive maintenance services* will be progressing in time in parallel with the proper definition of the related technologies (heat pumps, PVT systems and Lithium-Ion batteries). The steps as such are listed below:

- Identification of available input from models and sensors: Some information has already been provided. More detail will be specified.
- Definition of KPIs related to the faults to be predicted. The level of detail of the model and real data to be provided from the monitoring phase will determine the depth of the faults analysis.

- Fault Modes Effect and Criticality Analysis: This is connected with step 5 of the RCM and FMECA methodology (described in section 4.6.3.1.2)
- Fault scenarios identification: These will be identified in parallel with the fault modes effect and criticality analysis.
- Algorithms development. Implementation of predictive maintenance tool: Several algorithms will be developed for the different faults. They will be integrated into the predictive maintenance tool.

4.6.6 Structural view and integration points

TE-15 Predictive Maintenance Tool will be integrated in the general architecture of META BUILD project, together with the rest of technologies and services. Figure 34 shows the main structural view of TE-15 in connection with the relevant technologies that will be installed in Croatia and Spain pilots.

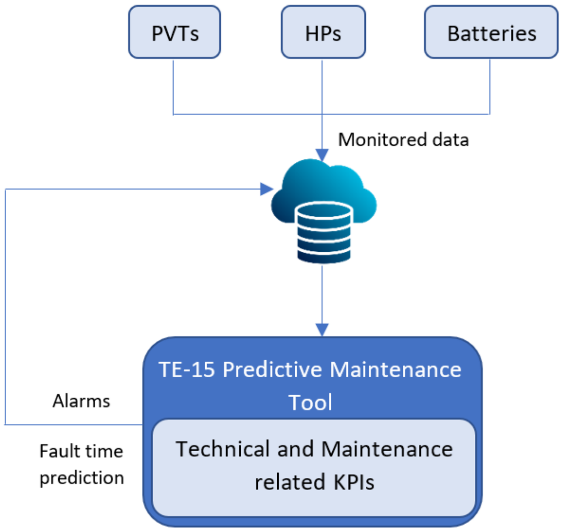

Figure 34 Predictive Maintenance Tool structural view

PVTs:

- TE-7: PVTs with direct lamination aluminum absorber crystalline silicon unglazed collector (TE-7).
- TE-8: Air based PVTs.

HPs:

- TE-2: District - heating-connected Heat Pumps.
- TE-6: Dual source Heat pump (DSHP).

Energy storage batteries:

- TE-9: Second life batteries.

Following the RCM methodology, the predictive maintenance tool focuses on detecting and predicting failures that should trigger the maintenance actions defined in the FMECA.

Data from the three technology types (PVT, HP and batteries) will be monitored at the respective demonstration sites. It is expected that this data will then be stored in a cloud database (or similar) to be managed. TE-15 will normally receive this data via API and use it to calculate technical and maintenance related indicators by comparing these real values against theoretical ones from models. The deviations detected will be used to provide a series of alarms when potential faults are detected. The proactive maintenance tool will provide two main types of outputs: (1) an estimate of the time remaining before the potential failure can occur, so that maintenance strategies can be put in place, (2) an alarm warning that some action must be taken to avoid a severe damage to the equipment or an unplanned shutdown.

4.6.7 Interoperability considerations and preliminary findings

Models will be developed to define the theoretical behaviour of the PVTs, HPs and batteries from the Croatian and Spanish demo sites. The minimum data points required for these models have already been identified, together with the time interval for the historical data and the data granularity needed for the predictive algorithms that will constitute the Proactive Maintenance Tool. The list of required data points is included below:

Data points needed for the heat pumps:

- Condenser mass flow.
- Inlet temperature at condenser side.
- Outlet temperature at condenser side.
- Electricity consumed by compressor.
- Evaporator mass flow.
- Inlet temperature at evaporator side.
- Outlet temperature at evaporator side.

Data points needed for the PVTs:

- Inlet temperature.
- Outlet temperature.
- Global incident solar irradiance on collector plane.
- Electrical power production.
- Thermal power production.
- Mass flow rate matrix 9 PVT panels.
- Wind velocity on the collector plane.
- PVT thermal efficiency.
- PVT electrical efficiency.

Data points needed for the batteries:

- Voltage at cell / battery terminals.
- Current output.
- SOC (estimated by BMS).

4.7 Building Digital Twins

4.7.1 Overview

This section is aligned with T4.6 – “Digital-twin for buildings optimised operation, fault detections and predictive maintenance” aiming to develop an enhanced building Digital Twin (DT) tool for building and facility managers, leveraging smart devices, data analytics, and intelligence techniques for building electrification.

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The tool will combine big data, algorithms, and hybrid models for dynamic smart building operation, enabling real-time monitoring, decision making, and mid-term planning for electrification. Advanced functionalities will be developed in these areas:

c) Energy use planning with daily and weekly recommendations for prioritizing energy uses, load-shifting using DR schemes (e.g., real-time pricing tariff emulation), and local PV production forecasting.
c) Optimised operation through algorithms and machine learning techniques that exploit physical and data-driven models for building performance predictions with an occupant-centric approach.
c) Predictive maintenance by developing metamodels that will enable real-time fault detection, diagnosis, and prediction of critical equipment's remaining useful lifetime.

These functionalities aim to achieve energy savings and smart building operation and maintenance while addressing user needs and providing grid flexibility. The operational DT with the three core modules will be deployed in Front Runner 6 (Spain) for their validation.

4.7.2 Starting status, description and constraints

The new extension of TECNALIA's headquarters in Donostia-San Sebastián, Spain, will add 1200 m^2 to the existing 4500 m^2 building, featuring offices, laboratory facilities, and underground car park. The extension will be energy-efficient and connected to the existing building's energy systems, with a focus on electrifying thermal energy demand.

The initial operation of the Air Handling Unit (AHU) is configured as a Constant Air Volume (CAV) system, with airflow rates determined according to Spanish standards, utilizing the indirect method to define ventilation requirements based on maximum occupancy within the specified spaces. In order to be able to implement the optimised operation further explain in next sections, some controllers have been installed in the office space that enable sectorised operation of HVAC terminal units. In addition, the initial CAV system was modified before implementation and the office area are now covered by Variable Air Volume (VAV) dumpers. This new construction building, equipped with high-performance systems and a current Building Management System that centralises building and system data, proposes an optimised operation module. This module is to be fine-tuned by incorporating additional features beyond those specified in the grant agreement, such as occupant-centric approaches, to enhance the actual performance of the HVAC system.

Front Runner 6 will allocate the installation of the Dual-Source Heat Pump (DSHP) (TE-6) and PVT (TE-7) developed under the META BUILD project scope, together with the building DT (TE-16). Due to the limited capacity (10 kW) of the DSHP prototype compared with the heating load expected for the whole FR6, the DSHP will only serve the air heaters in the laboratory's facilities. The rest of the heating demand will be supplied by means of the existing biomass boiler. Given this context, the energy use planning for electrification of the thermal demand will only be deployed in the laboratory's facilities. In this sense, the proposed models will just characterise the heating demand of this zone. In this sense, it is important to highlight that this module aims to generate recommendations for decision making, but it will not operate the air heaters whether the DSHP or the solar systems, as it is not the scope of the module.

The building currently uses Tridium as the BMS platform, specifically the Niagara system [77], which manages the basic building operations. The field protocol used is MODBUS RTU [78] and a MODBUS-IP gateway has been implemented to facilitate communication between the META BUILD DT and the BMS. The integration of BMS data with advanced DT sensors represents a significant enhancement in building performance monitoring and optimisation capabilities. The existing BMS infrastructure provides comprehensive coverage of critical HVAC components, including detailed monitoring of the AHU return air CO_2 levels, fan-coil operations, and thermal energy measurements across heating and cooling circuits. This foundation is strategically augmented with additional smart sensors deployed as part of the DT implementation.

The optimised operation module will be deployed in the office area, as it represents a suitable space for occupant-centric optimised operation techniques. This area exhibits high variability in occupancy levels, indicating a need for the optimisation of HVAC systems to operate in accordance with occupancy fluctuations. The entire open office space will be considered for the deployment of this module, along with a single meeting room. The latter will serve as a comparison for the operation of meeting rooms using an occupant-centric approach. The performance of this room will be compared to that of an adjacent meeting room, which has similar features but will be operated according to the baseline. The predictive maintenance module will be deployed for a specific case-study zone in the office area. Two equipment, consisting of a Fan Coil Unit (FCU) and a Variable Air Volume (VAV) dumper will be considered for this purpose.

4.7.3 Core technology aspects

4.7.3.1 Energy use planning module

The energy use planning module will provide recommendations for prioritizing energy uses (from DSHP and PV production), forecasting local PV production and suggesting load-shifting using Demand Response schemes based on electricity prices. The objective of this module is to improve energy efficiency, reduce energy consumption and enhance electrification of the thermal demand by integrating predictive capabilities and analysing loads. Thus, only HVAC systems will be considered.

Modelling approach

Simplified models such as Energy Signature (ES) will be developed for long-term characterisation of thermal loads. In this project, the models will be used to analyse weekly energy patterns. ES models are considered black box models that relate the average outdoor temperature to the energy consumption of buildings for thermal conditioning. It is a proven methodology referenced in international M&V frameworks (i.e., IPMVP [1]). ES are generated by linear regressions that make a simplified assumption of a linear relationship between temperature and heating energy demand, offering a good balance between some level of physical representation (the climate dependence of space heating) and an immediate estimation based on real data sets for a specific building typology, presenting an appropriate trade-off between model accuracy and computational time **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**.

ES models are not applicable for consumptions not directly related to outdoor temperature. Identifying the variables that allow their use to be normalised is necessary. Regression models are useful to identify dependency relationships if they are applied to the variable to be normalised and the exogenous variables that are assumed to have a significant influence. These parameters with a significant effect on the variable to be normalised should be included in routine adjustments.

This model assumes that the energy patterns related to the thermal conditioning of buildings resemble one of the behaviours identified in Paulus et al. (2014) **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. The linear regressions observed are known as change point regression models, these change point slopes being those values of the exogenous variable where consumption is predicted by a new formula. The section that is less related to the outdoor temperature and, therefore, has a lower slope (or even a flat section) is related to mild outdoor temperatures, where there is no thermal consumption, or where consumption is constant in the face of variations in outdoor temperature. On the other hand, the section that is more directly related to outdoor temperature variations is related to cooling (high temperatures) or heating (low temperatures) consumption. The models can be defined by three, four or five parameters depending on the complexity and trend of the building loads.

Once it has been established which variables are significant, the suggested calculation method for generating ES is based on the ASHRAE change point models **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. It is formulated by means of a segmented linear regression or piecewise regression, where a linear regression model is fitted to data that have one or more points where the slope changes. For implementation, there are libraries and mathematical implementations such as the Python *piecewise regression* function **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.** that performs mathematical implementation of regression models.

Once the behavioural models have been obtained, projections can be made from the baseline period to the demonstration period based on the identified variables. This approach addresses the characterisation of energy use for thermal conditioning at both building and subsystem level, addressing the impact quantification of the application of energy saving measures when comparing the pre- and post-implementation periods and the identification of unusual energy performance of subsystems.

ES methodology can provide satisfactory results for monthly and seasonal data as demonstrated in several investigations **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.-Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. It also allows for more accurate analyses if daily or hourly aggregations are used, so that more detailed information on typical energy demands can be provided compared to monthly or weekly patterns **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. In fact, data clustering is proposed as a method for classifying energy consumption patterns, this process could be done per day of the week, hourly timeslots (working and non-working periods), or other significant parameters. Weather data can be directly obtained from the local weather station installed in FR6. For other case-studies where there is no data availability, open-source weather datasets can be used instead. In fact, weather forecasts from open-source datasets could be implemented for heating load prediction in a defined time horizon.

Regarding the production side, day-ahead forecasts must also be obtained for: PV electricity production, DSHP and biomass boiler thermal demand in laboratory facilities, DSHP electricity consumption. For that purpose, two approaches will be considered depending on the availability of monitored data:

- Simplified physics-based models including physics equations (e.g. COP dependency on outdoor conditions) with weather forecasts.
- Data-driven approaches (e.g., linear regression, Autoregressive integrated moving average – ARIMA [80]) based on monitored data (e.g., outdoor temperature, solar radiation, PV production, DSHP production, etc.).

Load-shifting analysis

The proposed methodology includes characterizing heating demand to identify deviations and unusual operations. The analysis will compare PV production, heating demand forecasts for DSHP and biomass boiler, and electricity prices to identify optimal time slots for load-shifting.

Different heating scenarios will be compared by analysing the energy cost of meeting the thermal demand using the DSHP (considering electricity prices forecast) and the biomass boiler. The PV production forecast will be analysed and integrated with the DSHP consumption. An optimisation problem will be deployed to determine the time slots when PV production is high, and electricity prices are low to optimise the use of the DSHP. The module will recommend load-shifting strategies to Prioritise the use of PV production for the DSHP during periods of low electricity prices, which can help reduce overall energy costs. Simultaneously, the module will evaluate the efficiency and cost-effectiveness of using the DSHP versus the biomass boiler under different scenarios for the defined period. As a result, the module can effectively recommend load-

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shifting strategies enabling the facility manager to make informed decisions on optimizing energy use and reducing costs. Algorithms like linear programming and genetic algorithms will generate optimised energy use plans, that will be tested and validated.

Energy use planning reports

This module will generate two types of energy use planning reports that will be available through the DT platform. The first one will consist of daily energy use planning reports including daily recommendations for peak demand adjustments as a result of the load-shifting analysis with forecast models. The purpose is to provide recommendations and adjustments with a focus on immediate actions to optimise energy usage for the next day. These reports shall contain, as a minimum, the following information:

- Actual and future date (corresponding to the next day).
- PV production forecast for the next day.
- Thermal demand forecast for DSHP and biomass boiler for the next day.
- Electricity price forecast for the next day.
- Recommendations: load-shifting suggestions.

Additionally, weekly energy use analysis reports will be automatically generated for analysing performance over the past week and identify trends by means of the ES models. It will include a summary of deviations and the overall performance of the heating demand.

- Date range (start and end date).
- Actual vs. forecasted data from the last week (PV production, thermal demand, electricity price, weather, etc.).
- Identification of deviations and anomalies based on ES models from the last week.

Data requirements

The weather forecast data, and the electricity price forecast data will be obtained from open-source datasets and implemented for the production and energy demand predictions. Energy data for the DSHP, the biomass boiler and PV, will be obtained with hourly granularity, together with the energy demand of the air heaters in the laboratories. Monitored data requirements encompass data pre-processing from monitored data, statistical, and visual data analysis to detect deviations. If historical data are not available at the beginning of the model's development, synthetic data from physics-based models integrating the META BUILD solutions could be employed.

4.7.3.2 Optimised operation module

The proposed methodology focuses on implementing occupant-centric strategies in a multi-occupancy space to optimise building energy use and occupant comfort simultaneously. The main objective of this module is to operate HVAC terminal units to meet indoor thermal and ventilation requirements based on occupancy levels. For that purpose, a virtual zone layout is defined in the office area of FR6 to operate accordingly with occupancy distribution. The HVAC terminal units of FR6 consist of 4-pipe FCUs with heating and cooling batteries and VAV units for the AHU. Two occupant-centric strategies are proposed for each system to operate the office space considering the virtual zones layout.

Virtual zones layout

This module is intended to operate in shared spaces (i.e., office area, waiting rooms, etc.) aiming to reduce occupancy disturbances when optimizing HVAC terminal units' operation. For that reason, a virtual zone setup is proposed to obtain monitored data from each zone, enabling sectorised operation based on estimated or predicted occupancy and building performance.

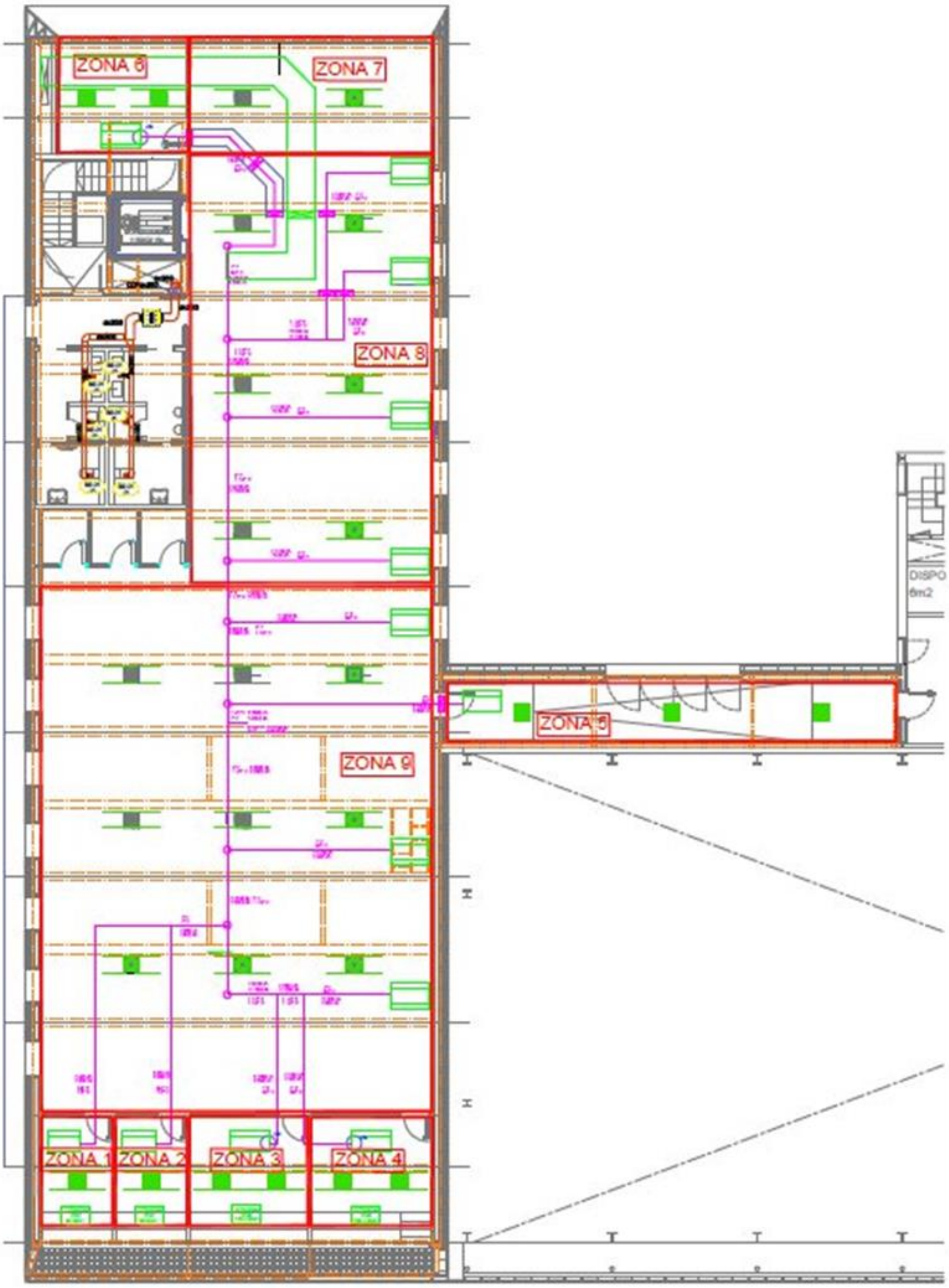

Figure 35 Office floor plan with HVAC sectorisation and virtual zones layout in Front Runner 6

The virtual zones layout is defined considering spatial arrangement in the office floor, considering physical spatial limitations (such as inner walls); and the virtual zones considered for the sectorised operation of the systems. In this sense, there is an open working zone (430m^2), where 3 virtual zones have been established. Each zone has a proper and spatial dedicated controller, that governs the FCUs and VAVs. One zone poses special thermal behaviour because it is partially surrounded by a glazed envelope. This zone is notably smaller than the other two and will be conditioned by one dedicated FCU and one set of VAVs. The other two zones are bigger zones that are foreseen to have a similar thermal behaviour all over the zone, accounting for 3 FCUs and sets of VAVs each. The HVAC systems are sectorised accordingly with the virtual zones layout (see Figure 35).

Virtual zones occupant-centric model predictive control for fan coil units' operation

A virtual zone occupant-centric model predictive control (VZOC-MPC) is proposed for the optimisation of the FCUs operation. The FCUs air temperature setpoints will be adjusted for each virtual zone depending on predicted occupancy levels and building thermal dynamics. The temperature setpoints and setbacks will be optimised to ensure comfort levels in occupied virtual zones while achieving energy cost savings in non-occupy virtual zones.

Grey-box models will be employed for the building performance forecasting. A Resistance-Capacitance (RC) approach for multi-zone spaces is proposed [79]. It will incorporate parameters such as thermal dynamics, energy flows, building envelope characteristics, internal heat gains (including those estimated from occupancy forecasting), and ventilation requirements. The RC model will be validated using historical data and real-time measurements. Other simplified approaches could be implemented for this purpose, such as linear regression models or ARX [81], depending on available monitored data.

The occupancy levels will be analysed by means of radar and noise sensors that will integrate an internal logic to estimate the number of occupants in each virtual zone. Considering the strong stochastic characteristics of occupancy behaviour, an interval prediction (based on pre-defined occupancy levels, i.e., high occupancy, medium occupancy, low occupancy, non-occupancy) is proposed to provide more flexibility for control-signal decisions **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. Thus, occupancy models will be developed to forecast occupancy levels and generate occupancy schedules which are crucial for spaces with significant occupancy variations. A stochastic data-driven approach is proposed by using calibrated real monitoring data (occupant presence and counting). Markov chains or hidden Markov chains models are proposed for short-term predictions as they can reflect the randomness and autocorrelation of occupant movement and have demonstrated to reach high prediction accuracy for HVAC system control **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. For long-term forecasting, Seasonal Autoregressive Integrated Moving Average (SARIMA) models [82] are proposed for analysing and predicting seasonality on occupancy patterns. Given the building dynamics, it is unnecessary to consider small and temporary occupancy variations for adjusting HVAC settings. Thus, the short-term predictions will neglect small occupant variations (one-person) in a 15-minute horizon. The RC model accuracy will be leveraged by including the occupancy heat gains estimated from occupancy forecasts.

An MPC approach is proposed to address the virtual zones operation based on occupant-centric and energy saving strategies. The setpoints and schedules of the FCUs will be adjusted based on occupancy model outputs for enhancing thermal occupants' comfort and reducing energy consumption related to FCUs operation in the virtual zones' layout. A weighting factor will be included in the cost function of the MPC formulation to Prioritise thermal comfort when occupancy is expected in the virtual zone. The control problem will include some constraints related to equipment (i.e., maximum capacity, DSHP and biomass boiler schedules, etc.) and to thermal boundaries. Adaptative setpoints and setbacks for FCUs will be proposed for different occupancy levels and distribution in the office area within the virtual zones.

Virtual zone demand-controlled ventilation based on occupancy levels for VAVs operation

The VAVs operation will be controlled by means of a Virtual Zone Occupant-Centric Demand-Controlled Ventilation (VZOC-DCV), based on ASHRAE RP-1747 CO_2-based Demand Controlled Ventilation for Multiple Zone HVAC Systems in Direct Digital Control Systems **Σφάλμα! Το αρχείο προέλευσης της αναφοράς**

δεν βρέθηκε.. This methodology is still pending for adoption on ASHRAE Guideline 36 as its efficacy in real-world applications must be still verified **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. The proposed control logic from ASHRAE uses trim and respond logic to dynamically adjust VAV terminal units' minimum airflow setpoints based on zones' ventilation requirements considering CO_2 concentration. As highlighted by previous studies, there exists potential for the data from CO_2 sensors to be replaced with infrastructure which count occupants directly for DCV purposes, which will leverage the control logics features. Further information on the DCV control logic is available in O'Neill et al. **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.** and the details of the trim and response sequence can be found from the ASHRAE Guideline 36 **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**. According to Hobson et al. (2025) **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.**, the minimum setpoint is the one being adjusted. In a VAV AHU system, space conditioning and ventilation are interconnected, allowing the zone's primary airflow to exceed the minimum level by opening the VAV terminal units' dampers when necessary to meet conditioning demands. An analysis of occupancy profiles and ventilation requirements will be performed to decree whether it is worth including occupancy predictive models for forecasting day-ahead arrivals and departures.

Data requirements

To enable VZOC-MPC, several building and occupancy data must be monitored before and after implementation for the development and calibration of the predictive models and the deployment of the MPC algorithm. The building data consists of thermal consumptions at zone level, indoor temperature, relative humidity, occupancy levels (estimated from radar and noise sensors in this case), FCUs setpoint temperature, and other energy-related parameters at zone level that could rely on the zone performance. A 15-min granularity is required with a virtual zone or physic zone desegregation. Meanwhile, the VZOC-DCV data requirements consist of people counting (zone population) or CO_2 concentration instead. Additionally, CO_2 concentration in supply air, supply air temperature and airflow across the entire outdoor air intake will enhance the control logics performance for operating the AHU in accordance with the estimated zone requirements. The data should be provided with a 15-min granularity if possible.

The monitored data must be pre-processed and analysed via statistic and visual data analysis in order to identify patterns, deviations, or any singularity that could affect the predictive models.

4.7.3.3 Predictive maintenance module

Maintenance of systems/equipment linked to the services/processes taking place in tertiary buildings (e.g. HVAC) is still solved through preventive maintenance procedures. These strategies guarantee adequate levels of equipment availability and reliability. However, they do not allow for the minimisation of cost, or the consumption of resources (e.g. spare parts, human resources) dedicated to maintenance tasks. Thus, it is necessary to enable the transition to predictive maintenance strategies, which requires predictive models and dedicated supervisory systems with specific functionalities. Existing solutions developed for FDD systems for building HVAC equipment have traditionally relied on predictive capabilities derived from physics-based models and/or knowledge-based models (e.g. expert rules). However, all of these approaches have limitations that constrain their applicability in real-world conditions (e.g. complexity and high costs associated with developing physical models for equipment degradation, limited predictive capacity and accuracy).

As a solution for these limitations the META BUILD Digital Twin incorporates a dedicated module for predictive maintenance, including anomaly detection and fault diagnostics functionalities for the critical equipment of HVAC systems. By utilizing real-time information from sensor networks regarding the operational parameters of the monitored equipment, the system can characterise their status and generate recommendations. To achieve this, the developed solution will exploit an ecosystem of models created through a combination of historical data, supervised, semi-supervised, and unsupervised classification techniques, as well as physics-based energy models.

More specifically, anomaly detection models will be developed through unsupervised classification algorithms (Local Outlayer Factor [90], OneClass Support Vector Machine-SVM [83], Isolation Forest [84], Generative Adversarial Networks [85], etc) and fault diagnostics models will exploit supervised and semi-supervised classification algorithms (Random Forest [86], SVMs [87], Ensemble methods [88], different architectures of neural networks, etc). To ensure system functionality under real-world conditions, characterised by limited availability of labelled data specially for faulty operational states, metamodels derived from physics-based models (using Modelica [89]) of HVAC equipment and machine learning techniques will be hybridised. The integration of physics-based models will address the limitation posed by the absence of labelled historical data for anomalous operating states.

The developed solution will be deployed for validation in the office zone of the FR6. To that end anomaly detection and diagnostics functionalities will be developed for the FCUs, the AHU and the ventilation air distribution duct network and dampers, possibly including among other the following diagnostics capabilities.

- Fan coil heating/cooling coil fouling.
- Fan coil faulty fan.
- Fan coil faulty control.
- AHU filter clogging.
- AHU faulty fan.
- Dampers faults (tightness degradation, blocked position, faulty control).

The model's development and validation will be based on the information collected by the existing sensor network connected to the BMS and by dedicated sensors directly integrated into the DT of the FR6. The evaluation of the quality of the predictive capabilities of the models will be based on metrics such as accuracy, precision and recall. Meanwhile the impact of the predictive maintenance functionalities to be deployed will be measured in terms of the availability/reliability and the maintenance costs of the supervised equipment.

4.7.4 Technology progress and status

The FR6 is a new constructed building that, at the time of this deliverable's submission, had not yet been occupied. It will be officially launched in May. All the thermal production equipment, AHU and distribution systems envisaged in the initial design of the building are installed and working properly. The modifications to the initial project for the sectorised operation have also been completed. The network and BMS connections are operational. Furniture and aesthetic details are still to be included.

At this point, there is still no data acquisition from the monitoring system, resulting in a lack of historical data necessary for developing data-driven models for building performance, occupancy predictive and predictive maintenance purposes. This process requires several months of data, ideally covering the most critical periods of operation, such as the winter months in this case.

The DT architecture has been defined as shown in Figure 36, describing the interoperability between the digital solutions (including DT interface, the three advanced modules and the common environmental data) and the physical solutions (the DSHP, PVT, the office building and the monitoring system). The DT modules (energy use planning, optimised operation and predictive maintenance) are in a conceptual stage, where the methodologies, tools and approaches have already been defined in the previous section. At this stage, the as-built BIM model of the new construction building is finished. It will be further enhanced by integrating a specific META BUILD BIM layer including sensor information.

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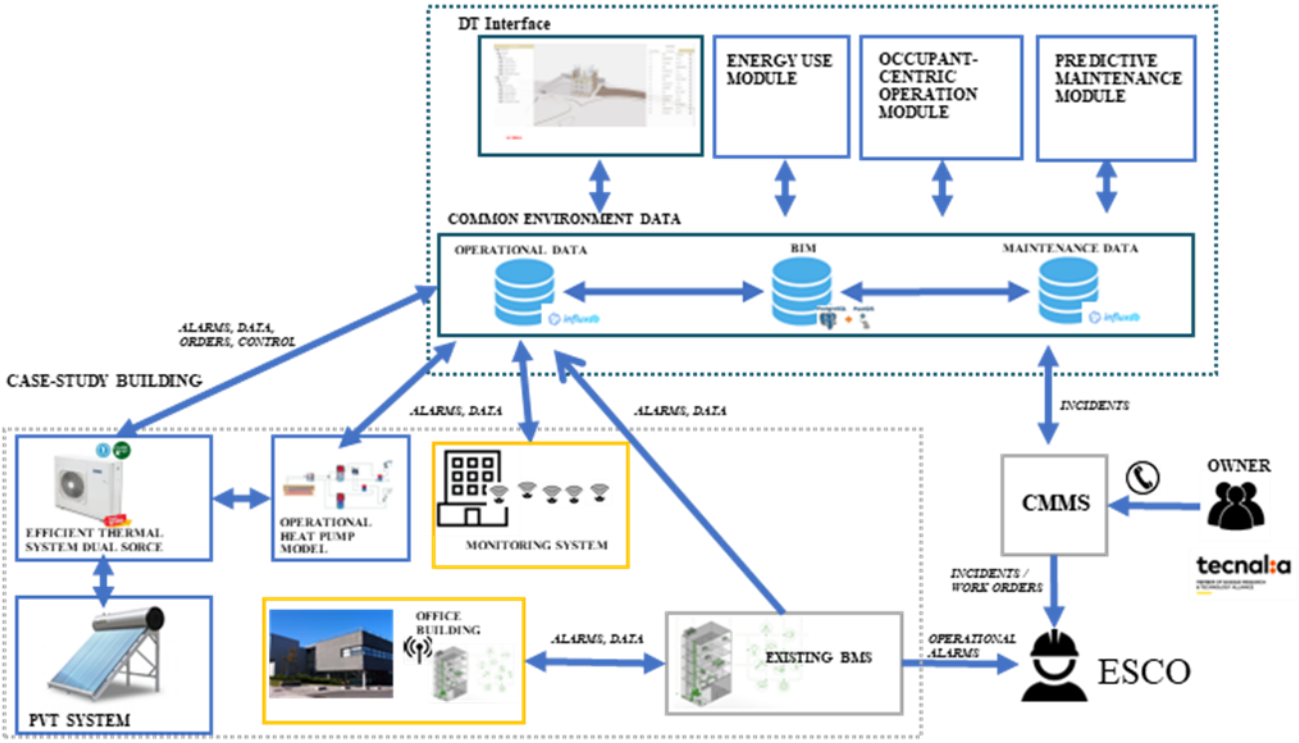

Figure 36 META BUILD Digital Twin architecture proposal for Front Runner 6

The monitoring system being implemented in TECNALIA's headquarters extension for Front Runner 6 consists of an integrated solution combining the existing BMS with new smart sensors and control capabilities. It will serve as the barebone of the DT, enabling real-time awareness of building performance, occupant comfort, and predictive maintenance. This integrated approach allows the DT to leverage both traditional BMS data streams and advanced IoT sensor inputs, creating a more robust and accurate model for building performance optimisation. In the case of the optimised operation module, it will automatically adjust building systems through BMS integration, creating a dynamic balance between comfort and energy optimisation. The sensor network has been carefully designed to address several key aspects: IEQ, energy efficiency and predictive maintenance.

For instance, while the BMS monitors basic ventilation levels in the office space, the DT extends this capability with advanced environmental quality monitoring through multi-variable sensors that track CO_2, PM, VOC, noise levels, and occupancy patterns. In addition, traditional thermostats are complemented with META BUILD sensors, creating a more granular understanding of indoor environmental conditions. The fan-coil monitoring strategy is particularly noteworthy, where a reference unit will be extensively monitored for predictive maintenance modelling, measuring supply air temperature, flow rates, and thermal energy transfer in both heating and cooling modes. This data is further enhanced by electrical consumption monitoring at both equipment and floor levels.

The monitoring infrastructure for TECNALIA's headquarters extension has reached a significant operational stage, with the core systems now collecting and processing data. The integration between the DT and the building's BMS has been successfully established through MODBUS-IP protocol, enabling seamless data exchange and control capabilities. This bidirectional communication architecture represents a crucial advancement, allowing not only passive monitoring but also active control interventions through strategic BMS set-point adjustments. The system implements a sophisticated authorisation framework that carefully manages these control capabilities, ensuring that automated interventions occur only when explicitly permitted and under strict privacy protocols. Data quality assurance processes have been implemented at initial levels, from sensor-level validation to aggregated data verification, ensuring the reliability of information flowing through the system. A fundamental visualisation dashboard is now operational, providing stakeholders with real-time insights into building performance metrics. This current implementation phase establishes the foundation for more advanced features planned in the DT roadmap, including AI-driven optimisation algorithms and predictive maintenance capabilities. The system's architecture has been deliberately designed to be extensible, allowing for the progressive integration of additional sensors (e.g. smart Matter sensors) and control capabilities as the project evolves, while maintaining robust security and privacy controls that protect sensitive operational data and user information.

Currently deployed sensors in the office area are listed below:

- Custom decibel sensors in the office area:
    - Used for noise level monitoring.
    - Include algorithms for occupancy counting based on sound patterns.
- Environmental monitoring sensors:
    - Meteorological station for PM, Temperature and Humidity.
    - Indoor CO_2 sensors (mh-z19b-co2).
    - Battery-powered Temperature and Humidity sensors.
    - Sensirion SGP40 Volatile Organic Compounds (VOC) sensors.
    - Interior PM sensors.
- Presence detection:
    - Radar presence sensors (Sonoff SNZB-06P).
- Energy monitoring intelligent electric sockets:
    - Used to monitor punctual electric loads.

The monitoring system implements a four-layered architecture as shown in Figure 37.

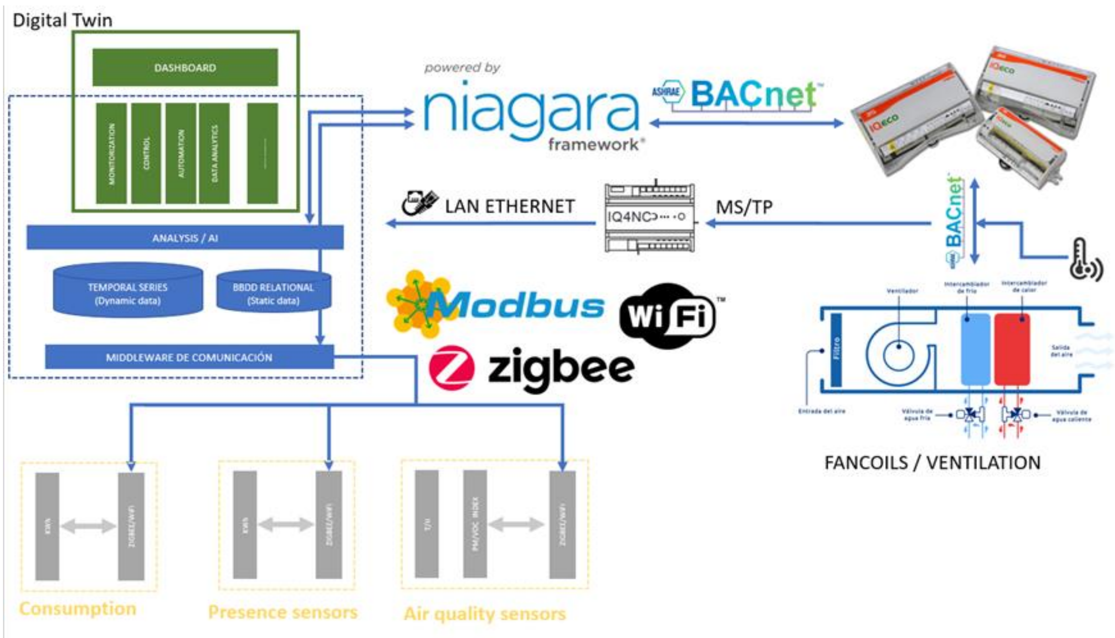

Figure 37 Data collection and analysis architecture for FR6

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The overview of the architectural layers is the following:

1. Communication Layer:

- IoT middleware based on WiFi and Zigbee sensors.
- MQTT gateway for data collection.
- Node-RED for data extraction and processing.

2. Storage Layer:

- InfluxDB for time-series sensor data.
- PostgreSQL for BIM model data.

3. Analysis Layer:

- Python microservices for AI algorithm development.
- Data quality assurance flows.
- Data aggregation capabilities.

4. Digital Twin Visualisation & Interaction Layer:

- BIM model visualisation interface.
- Real-time 3D building representation.
- Interactive dashboards for:
  - Energy performance monitoring.
  - Environmental conditions.
  - Equipment status.
  - Occupancy patterns.
- Control interfaces for the optimised operation module:
  - Monitoring Zone Occupant-Centric MPC (MZOC-MPC) for FCUs temperature setpoint adjustment.
  - Monitoring Zone Occupant-Centric Demand-Controlled Ventilation (MZOC-DCV) for VAVs airflow setpoint adjustment.
- Decision support tools:
  - Predictive maintenance alerts.
  - Energy use planning recommendations.

The DT implementation employs a sophisticated four-tier data architecture designed for scalability, reliability, and real-time processing capabilities. At its foundation, the Communication Layer orchestrates data collection through a hybrid network of WiFi and Zigbee sensors, ensuring robust connectivity while optimizing power consumption. This layer leverages MQTT protocol for efficient data transmission, with Node-RED providing flexible data extraction and initial processing capabilities, enabling seamless integration of diverse sensor types and protocols. The collected data flows into the Storage Layer, where a dual-database approach is implemented: InfluxDB handles time-series data from sensors with high-performance query capabilities for real-time monitoring, while PostgreSQL manages the structured BIM model data, maintaining the digital representation of the building's physical and operational characteristics. The Analysis Layer places on top of this foundation, employing Python-based microservices to implement AI algorithms for predictive maintenance and optimisation, while ensuring data quality through automated validation flows and intelligent aggregation processes. To handle the potential massive volume of sensor data, the system will specify a sophisticated Big Data architecture leveraging rs-delta (a native Rust library for Delta Lake, with bindings into Python [91]) for efficient data ingestion into Azure Data Lake Storage Gen2 [92], enabling scalable data processing and long-term storage capabilities. The implementation of Delta Lake technology provides Atomicity, Consistency, Isolation, and Durability (ACID) transactions, schema enforcement, and time travel capabilities, ensuring data reliability and versioning control. For AI model lifecycle management, MLflow [93] has been integrated to track experiments, package code into reproducible runs, and manage model deployments, while providing a central model registry that handles model versioning and stage transitions (from development to production). The system also incorporates automated CI/CD pipelines for model deployment, ensuring consistent quality and performance monitoring of AI solutions in production.

The fourth layer acts as the user interface and visualisation platform, integrating all underlying data and analytics into an intuitive, interactive environment. It provides both 2D and 3D representations of the building, allowing users to navigate through different spaces while accessing real-time data and control capabilities. The BIM integration enables spatial context for all sensor data and building systems, making it easier to understand and manage building operations. The DT graphical user interface serves as a comprehensive command centre, seamlessly connecting the building's physical and digital elements through an intuitive, role-based interaction platform. At its core, the interface leverages the 3D BIM model as a spatial navigation framework, allowing users to naturally traverse through the building's digital representation while accessing real-time data from the extensive sensor network. This spatial context is enriched with dynamic dashboards that visualise environmental conditions, energy performance, and system status through interactive trend displays. The control interface provides authorised users with direct access to building systems, enabling both manual adjustments and automated optimisation through data-driven recommendations. Different user roles experience tailored views of the system, with facility managers accessing comprehensive technical controls and analytics, and operators focusing on day-to-day operations and alert management. This hierarchical approach ensures that each stakeholder can effectively interact with the building's systems while maintaining operational security and efficiency.

This comprehensive data and AI infrastructure creates a robust foundation for the DT, enabling sophisticated analysis and decision-making while maintaining system flexibility for future expansions and adaptations to new requirements within the META BUILD framework, such as the application of Big Data extensions. The architecture supports both batch and real-time processing scenarios, making it possible to combine historical analysis with immediate response capabilities for building optimisation. The architecture supports both batch and real-time processing scenarios, making it possible to combine historical analysis with immediate response capabilities for building optimisation.

4.7.5 Ongoing work

The next development phase of the monitoring system will focus on leveraging the established monitoring infrastructure to deliver advanced functionalities aligned with META BUILD's core objectives. The next steps for the modules' development are listed as follows:

- Data acquisition once the building is occupied.
- Conduct building performance and occupancy data analysis.
- Models' selection and development.
- Initial modules prototype:

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  - Energy use planning.
  - Optimised operation.
  - Predictive maintenance.
- Modules deployment will be phased over the next project stages, with initial focus on energy use planning, followed by optimised operation and predictive maintenance capabilities, and culminating in the full integration of all systems under a unified DT platform.
- Modules validation in FR6.

This roadmap ensures a progressive enhancement of building intelligence while maintaining operational stability and allowing for continuous validation and refinement of implemented solutions.

4.7.6 Structural view and integration points

The structural view and integration points of the DT service are detailed in previous section 4.6 (see Figure 36 and Figure 37). The DT implementation at TECNALIA's headquarters extension employs a sophisticated four-tier data architecture designed for scalability, reliability, and real-time processing capabilities.

4.7.7 Interoperability considerations and preliminary findings

The comprehensive data and AI infrastructure previously described, creates a robust foundation for the DT, enabling sophisticated analysis and decision-making while maintaining system flexibility for future expansions and adaptations to new requirements within the META BUILD framework, such as the application of Big Data extensions. Regarding each of the individual advanced modules integrated in the DT service, specific data requirements have been identified in previous sections (refer to core technology aspects) and have been further detailed in Table 7. In particular, the energy-use planning module can be easily replicable in other demonstrators with similar energy systems (i.e., different types of heat pumps or solar collectors) but specific models should be created if any other type of technology is used for space conditioning (e.g., district heating, gas boilers, etc.). In the case of the optimised operation module, the predictive models must be adapted to each specific case, as grey-box approaches are not directly applicable to different buildings. Further adaptation of the control logic must also be reviewed to adapt the optimised operation module to different buildings. This module could work in a coordinated manner with other control strategies applied at different scales, as it operates at the zone level and not at the building or system level. So other approaches could be integrated into the DT, by coordinating the new operational modules with the existing ones via the BMS and the common data layer. At this moment, the DT is fully interoperable in relation to META BUILD TE-6 (DSHP) and TE-7 (PVT). Additionally, the DT is conceived as an upper-layer solution capable of interoperating with existing control and management systems (e.g. BMS) through standard communication protocols. This approach will grant the predictive maintenance module access to information gathered by IoT sensor networks and enable it to generate recommendations to optimise maintenance interventions.

4.8 Summary of Technology Enablers Progress and Integration

This deliverable thoroughly documents the first development iteration and integration of the META BUILD technological enablers, clearly demonstrating their substantial role in advancing smart energy management, decarbonisation, and sustainability across diverse pilot settings in Europe. Throughout Chapter 4, each TE provider has outlined its initial technology status, presented core functionalities, described preliminary results, and discussed the structural view, integration potential, and interoperability considerations within the evolving META BUILD architectural framework.

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From the analysis provided in Section 4, it becomes evident that the technological enablers developed within META BUILD align significantly with the architectural framework defined in Chapter 2. Heat pumps, including brine-to-water, district heating-connected, MW-size reversible, inverter-driven, R290 monobloc, and dual-source/sink heat pumps, stand as foundational components for electrifying thermal loads in both residential and commercial buildings. Simultaneously, PVT solutions, storage systems—including innovative second-life battery solutions—and RES assets significantly complement these decarbonisation goals. The partners have detailed the structural components, emphasizing integration interfaces such as hardware control modules, API endpoints, cloud connectivity, and modular software solutions necessary for their effective integration.

A key theme consistently emerging across the provided descriptions relates to interoperability. Although considerable progress has been achieved regarding connectivity, data exchange mechanisms, and structural integration at a hardware level (e.g., API-based solutions), semantic interoperability remains an aspirational yet crucial objective for future phases. Initial assessments underline the challenges in standardizing data formats and ensuring coherent integration between heterogeneous systems, especially in multi-vendor environments. Such findings will guide further development, emphasizing the need for more detailed semantic definitions, standardised protocols, and refined data management platforms that could provide seamless, secure, and intelligent operations.

Future activities highlighted by TE providers emphasise deeper integration and iterative improvements. Ongoing work will further refine individual TEs by addressing identified interoperability gaps and expanding their operational capabilities through advanced analytics, predictive modelling, and automated control via Digital Twins and Model Predictive Control strategies. This aligns well with the project's broader goals—improving user comfort, optimising energy efficiency, and maximising decarbonisation impacts.

Looking forward, the following iterations (D4.2 – "META BUILD Digital Twin, data-driven services & apps for smart energy management, 2nd version" and subsequently D4.3 – "META BUILD Digital Twin, data-driven services & apps for smart energy management, final version") will build upon these foundational outcomes, progressively enhancing maturity, integration potential, and practical applicability. The forthcoming deliverables will encapsulate advanced developments, rigorous field validations, enhanced interoperability frameworks, and enriched data-driven services. Continuous stakeholder engagement, validation in pilot environments, and iterative refinement of technological enablers will ensure that META BUILD's final framework becomes scalable, robust, and widely replicable across the European building sector, thus decisively contributing to Europe's broader decarbonisation and sustainability objectives.

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5 Conclusions

This document represents deliverable D4.1 – "META BUILD Digital Twin, data-driven services & apps for smart energy management, 1st version" encapsulating contributions from multiple partners across the META BUILD consortium. It introduces the preliminary architectural framework, outlines key technological enablers, and establishes initial integration profiles aimed at electrification, renewable energy integration, and advanced energy management.

The deliverable clarifies how core technologies—including various types of heat pumps, photovoltaic thermal systems, second-life battery storage, and digital management solutions such as Energy Management Systems, Model Predictive Control, and Digital Twins—collectively contribute to META BUILD's overarching goal of decarbonizing building infrastructure. These technologies are meticulously structured within the project architecture, addressing vital issues such as energy efficiency, carbon footprint reduction, grid interaction, and occupant comfort.

From a structural and integration perspective, this deliverable emphasises robust connectivity among diverse hardware components and sophisticated digital management solutions. Communication standards are leveraged for seamless integration, promoting real-time operational monitoring and enhancing flexibility for future developments. However, semantic interoperability remains an identified area requiring further research and standardisation to fully capitalise on advanced predictive analytics, integrated control solutions, and automated operational strategies across diverse building contexts.

In terms of Business Use Cases, each scenario analysed in this document provides valuable insights into how TEs contribute towards energy optimisation, cost savings, improved environmental quality, and enhanced user experience. These scenarios underline the practical applicability and effectiveness of the proposed META BUILD solutions, showcasing pathways toward scalable and replicable solutions across residential, commercial, and industrial segments.

Looking ahead, the subsequent deliverable, will significantly expand upon the groundwork laid here by presenting a second iteration of META BUILD digital solutions. Specifically, the deliverable will detail advancements across several technical tasks (T4.1 – "Interoperability framework for electrified ready buildings", T4.2 – "Value-added services co-design & modelling framework for data-driven services", T4.3 – "Building as a whole: Services for optimal trade-off among comfort, energy & building performance", T4.4 – "Building as an active node: Services for demand response, grid interaction & flexibility planning", T4.5 – "Building electrification ecosystem: Serviced for the management of electrification technologies, RES integration & proactive maintenance", T4.6 – "Digital-twin for buildings optimised operation, fault detections and predictive maintenance"), offering refined and mature digital services and technological integrations developed through iterative design, feedback, and rigorous testing. These advancements will not only enhance interoperability and performance of the META BUILD architecture but will also address current challenges and limitations identified within this document.

Ultimately, this first version represents the foundational stage, setting the basis for subsequent enhancements and refinements. It paves the way toward the development of fully integrated and comprehensive solutions, driving towards the final, validated outcomes that will be documented in D4.2 – "META BUILD Digital Twin, data-driven services & apps for smart energy management, 2nd version" and D4.3 – "META BUILD Digital Twin, data-driven services & apps for smart energy management, final version", and ultimately facilitating a scalable and replicable framework for future sustainable, resilient, and smart energy-efficient buildings across Europe.

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Annex A

Table 7 META BUILD services data requirements

Services	Req	Data type	Unit of measurement	Level	Time Interval	Best Case Granularity	Worst Case Granularity
R290 brine-to-water HP	R1	Annual Heat Demand	kWh/a	per building	static	-	-
	R2	Nominal Supply Temperature	°C	per building	static	-	-
	R3	Max. Heat Load	kW	per building	static	-	-
	R4	Hourly Heat Load	kW	per building	Test Reference Year	per hour	per month
	R5	Ambient Temperature (Forecast)	°C	per location	forecast	1 hour	not available
	R6	Compressor speed (rps)	1/s	per heat pump	forecast	15 min	not available
District-heating-connected HPs	R1	Air temperature	degrees Celsius	boiler room's location	form October 2023 to October 2024	hourly	daily
	R2	Flow rate of the well	m³/s	well		every second	daily
	R3	Temperature of the well	degrees Celsius	well		minute	daily
	R4	Consumption	kWh		form October 2023 to October 2024	15 min	daily
	R5	Heating power	kWh		form October 2023 to October 2024	15 min	daily
	R6	Flow rate	m³/ΔT		form October 2023 to October 2024	15 min	daily
	R7	Total flow rate	m³		form October 2023 to October 2024	15 min	daily
	R8	Supply and return temperature	degrees Celsius		form October 2023 to October 2024	hourly	daily
MW-size reversible HP system	R1	Outdoor air temperature	°C	boiler room's location	2023-2024	hourly	hourly
	R2	Heating energy consumption	kWh	Submeters	2023-2024	hourly	hourly
	R3	Cooling energy consumption	kWh	Submeters	2023-2024	hourly	hourly
	R4	Heating energy consumption	kWh	Building	2023-2024	monthly	monthly
	R5	Cooling energy consumption	kWh	Building	2023-2024	monthly	monthly
	R6	Gas energy consumption	kWh	Building	2023-2024	monthly	monthly
	R7	Inlet/outlet heating water temperature	°C	Boilers and submeters	2023-2024	hourly	hourly
	R8	Inlet/outlet cooling water temperature	°C	Boilers and submeters	2023-2024	hourly	hourly

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	R9	Building areas	m²	Heated and cooled zones for each submeter	N.A.	N.A.	N.A.
Speed controlled/inverter-driven HP	R1	Energy consumption	kWh	per heat pump	2 hours	2 hours	2 hours
	R2	Temperature HP Set point	°C	per heat pump	1 hour	1 hour	1 hour
	R3	Temperature Outdoor	°C	Building	1 hour	1 hour	1 hour
	R4	Temperature Room	°C	per heat pump	1 hour	1 hour	1 hour
	R5	Domestic hot water	°C	per heat pump	1 hour	1 hour	1 hour
	R6	Mode of HP(heating or cooling)	-	per heat pump	1 hour	1 hour	1 hour
R290 monobloc unit for outdoor installation	R1	Hourly Heat Load	kW	per building	Test Reference Year	per hour	not available
	R2	Ambient Temperature (Forecast)	°C	per location	forecast	1 hour	not available
	R3	Ambient Umidity (Forecast)	%	per location	forecast	1 hour	not available
	R4	Ambient Light intesity (Forecast)	lux	per location	forecast	1 hour	not available
Dual Source/sink HP (DSHP)	R1	T_dshx_in	From MK7 Building	ºC	during operation	1 sec	15 sec
	R2	T_dshx_out	From MK7 Building	ºC	during operation	1 sec	15 sec
	R3	T_dem_in	From MK7 Building	ºC	during operation	1 sec	15 sec
	R4	T_dem_out	From MK7 Building	ºC	during operation	1 sec	15 sec
	R5	T_amb	From MK7 Building	ºC	during operation	1 sec	15 sec
	R6	RH_amb	From MK7 Building	%	during operation	1 sec	15 sec
	R7	m_w_dem	From MK7 Building	m3/h	during operation	1 sec	15 sec
	R8	m_w_dshx	From MK7 Building	m3/h	during operation	1 sec	15 sec
	R9	ΔP_dshx_w	From MK7 Building	kPa	during operation	1 sec	15 sec
	R10	ΔP_demand_w	From MK7 Building	kPa	during operation	1 sec	15 sec
	R11	W_hp	From MK7 Building	kW	during operation	1 sec	15 sec
Other RES - Thermally activated foundation	R1	Thermally activated foundation inlet temperature	ºC	per building	Period installed	10 min	hourly
	R2	Thermally activated foundation outlet temperature	ºC	per building	Period installed	10 min	hourly
	R3	Flow rate	m3/h	per building	Period installed	10 min	hourly
PVT-l (Liquid based PVT)	R1	Ambient Temperature	°C	per building	Period installed	15min	hourly
	R2	Plane of Array Irradiance	W/m2	per building	Period installed	15min	hourly

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	R3	Wind velocity on solar field	m/s	per building	Period installed	15min	hourly
	R4	PVT-l outlet temperature	°C	per PVT-l system	Period installed	15min	hourly
	R5	PVT-l mass flow rate	m3/h	per PVT-l system	Period installed	15min	hourly
	R6	PVT-l electrical power production	kW	per PVT-l system	Period installed	15min	hourly
	R7	PVT-l power thermal production	kW	per PVT-l system	Period installed	15min	hourly
PVT-a (Air based PVT)	**R1**	Ambient Temperature	°C	per building	Period installed	hourly	hourly
	R2	Global Horizontal irradiance	W/m2	per building	Period installed	hourly	hourly
	R3	Wind velocity on the roof level	m/s	per building	Period installed	hourly	hourly
	R4	PVT-a outlet temperature	°C	per PVT-a system	Period installed	hourly	hourly
	R5	PVT-a mass flow rate	m3/h	per PVT-a system	Period installed	hourly	hourly
	R6	PVT-a electrical power production	kW	per PVT-a system	Period installed	hourly	hourly
	R7	PVT-a power thermal production	kW	per PVT-a system	Period installed	hourly	hourly
Semantic interoperability enablers	**R1**	Type(s) of Services/Technologies used	text	building/front runner	static	-	-
	R2	Available Interfaces of TE	text; e.g. SG-Ready, BACNet, EEbus, KNX, ModBus..	per TE (HP's, RES, PVT or Storage technology)	static	-	-
	R3	Availability of Building Energy Management System (BEMS)	binary (yes, no)	building	static	-	-
	R4	Type of BEMS	text	building	static	-	-
	R5	Required Information for Service/Technology	text (this table)	use case	static	-	-
Building model for planning and MPC	**R1**	Building area	m2	whole building	static	-	-
	R2	Heating setpoint	°C	each room	static	-	-
	R3	Construction components	-	wall type (outdoor wall, internal wall, roof, ...)	static	-	-
	R4	Approximate shape	-	whole building	static	-	-
Enhancing Comfort, Energy & Performance	**R1**	Total active energy per phase and total	Wh	whole building	1 second	1 second	1 second
	R2	Total active returned energy	Wh	whole building	1 second	1 second	1 second
	R3	Current measurement	A	per location	1 hour	1 hour	1 hour
	R4	Voltage measurement	V	per location	1 hour	1 hour	1 hour
	R5	Active power measurement	W	per location	1 hour	1 hour	1 hour

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	R6	Apparent power measurement	VA	per location	1 hour	1 hour	1 hour
	R7	Power factor measurement	-	per location	1 hour	1 hour	1 hour
	R8	Network frequency measurement	Hz	per location	1 hour	1 hour	1 hour
	R9	CO2	ppm	per location	1 hour	1 hour	1 hour
	R10	Room Humidity	%	per location	1 hour	1 hour	1 hour
	R11	Room Temperature	Celcius	per location	1 hour	1 hour	1 hour
	R12	Noise level	dB	per location	1 hour	1 hour	1 hour
MPC control of MFH energy system	**R1**	PV-Production (Forecast)	W	building	3 days ahead	15 min	1 hour
	R2	Household El. Consumption (Forecast)	W	building	3 days ahead	15 min	1 hour
	R3	Ambient Temperature (Forecast)	°C	location	3 days ahead	15 min	1 hour
	R4	Global Horizontal Irradiation (Forecast)	W/m²	location	3 days ahead	15 min	1 hour
	R5	Diffuse Horizontal Irradiation (Forecast)	W/m²	location	3 days ahead	15 min	not available
	R6	Direct Beam Irradiation (Forecast)	W/m²	location	3 days ahead	15 min	not available
	R7	Zone Temperature(s)	°C	zone	during operation	15 sec	15 min
	R8	Zone Heat transfer coefficients	W/K	zone	static	-	-
	R9	Zone Thermal Mass	J/K	zone	static	-	-
	R10	Electricity Price (Forecast)	ct/kWh	building	1 day ahead	15 min	1 hour
	R11	Set Comfort Temperature	°C	zone	-	15 min	-
	R12	Min. Comfort Temperature	°C	zone	-	15 min	-
	R13	Max. Comfort Temperature	°C	zone	-	15 min	-
	R14	Number Occupants	integer	building	static	-	-
	R15	Internal Heat Gains (Occupancy/Appliances)	W	zone	-	15min	-
	R16	El. Battery SOC	%	building	-	15 sec	not available
	R17	El. Battery Capacity	Wh	building	static	-	not available
	R18	Mean Space Heating Storage Temperature	°C	building	during operation	15 sec	not available
	R19	Space Heating Storage Volume	m³	building	static	-	-

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	R20	Mean DHW Storage Temperature	°C	building	during operation	15 sec	not available
	R21	DHW Storage Volume	m³	building	static	-	-
	R22	Heat transfer coefficient of heat dissipators	W/K	zone	static	-	-
Demand response, Grid interaction & Flexibility Planning	**R1**	Electricity Demand Response Signals	Binary (on/off)	Home/HP	during operation	1 min	15 min
	R2	Electricity Price Forecast	€/MWh (24 values)	Market-wide	Daily forecast (D+1)	1 hour	1 hour
	R3	Heat Pump Operation Mode	Mode (on/off/idle)	Home/HP	During operation	1 min	15 min
	R4	Heat Pump Temperature Flow Control (Supply/Return)	°C	Home/HP	During operation	1 min	15 min
	R5	Heat Pump Consumption	kWh	Home/HP	During operation	1 min	15 min
	R6	Total House Consumption	kWh	Home	During operation	1 min	15 min
	R7	kWh of Load Shifted (Flexibility Response)	kWh	Home	During operation	1 min	15 min
	R8	Weather Forecast (Temp, Solar, Wind)	°C, W/m², m/s	Location	Forecast (1 day ahead)	1 hour	1 hour
	R9	Renewable Energy Generation	kW	Home/PV	During operation	1 hour	1 hour
Operation, control & proactive maintenance	**R1**	HP: Condenser mass flow	Kg/s	Home/HP	During operation	1 hour	1 hour
	R2	HP: Inlet temperature at condenser side	ºC	Home/HP	During operation	1 hour	1 hour
	R3	HP: Outlet temperature at condenser side	ºC	Home/HP	During operation	1 hour	1 hour
	R4	HP: Electricity consumed by compressor	kWh	Home/HP	During operation	1 hour	1 hour
	R5	HP: Evaporator mass flow	Kg/s	Home/HP	During operation	1 hour	1 hour
	R6	HP: Inlet temperature at evaporator side	ºC	Home/HP	During operation	1 hour	1 hour
	R7	HP: Outlet temperature at evaporator side	ºC	Home/HP	During operation	1 hour	1 hour
	R8	PVT: Inlet temperature	ºC	per building	Period installed	15min	hourly
	R9	PVT: Outlet temperature	ºC	per building	Period installed	15min	hourly
	R10	PVT: Global incident solar irradiance on collector plane	W/m2	per building	Period installed	15min	hourly
	R11	PVT: electrical power production	kW	per PVT system	Period installed	hourly	hourly
	R12	PVT: thermal power production	kW	per PVT system	Period installed	hourly	hourly

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	R13	PVT: Mass flow rate matrix 9 PVT panels	m3/h	per PVT system	Period installed	15min	hourly
	R14	PVT: Wind velocity on the collector plane	m/s	per building	Period installed	hourly	hourly
	R15	PVT: PVT thermal efficiency	%	per PVT system	Period installed	15min	hourly
	R16	PVT: PVT electrical efficiency	%	per PVT system	Period installed	15min	hourly
	R17	Battery: voltage at cell / battery terminals	V	per battery	during operation	1 min or less if possible	1 min
	R18	Battery: Current output	A	per battery	during operation	1 min or less if possible	1 min
	R19	Battery: SOC (estimated by BMS)	%	per battery	during operation	1 min or less if possible	1 min
Building Digital Twins	**R1**	PV-Production (Forecast)	W	per building	forecast data (1-7 days ahead)	15 min	1 hour
	R2	Electricity Price (Forecast)	€/MWh	per Building	forecast data (1-7 days ahead)	15 min	1 hour
	R3	Local energy production	W / kWh	per system (PV, PVT thermal and electrical, ST, DSHP, Biomass boiler, etc.)	during operation	15 min	1 hour
	R4	Electricity demand/consumption	W / kWh	per equipment (AHU heat exchanger, heating and cooling batteries for fan coils, fans, auxiliary, appliances, etc.) and per floor (parking, labs, offices, etc.)	during operation	15 min	1 hour
	R5	Thermal demand/consumption	W / kWh	per equipment (AHU heat exchanger, heating and cooling coils, etc.)	during operation (min 6 weeks for forecasting models)	15 min	1 hour
	R6	Weather data (ambient temperature, relative humidity, pressure, wind velocity and direction, solar radiation, PM2.5)	°C, %, Pa, km/h, W/m2, ppm	per location	during operation (min 6 weeks for forecasting models) and forecast data (1-7 days ahead)	15 min	1 hour
	R7	Control signals	-	per control equipment (VAV, AHU's fans, fancoil's fans, etc.)	during operation	15 min	1 hour
	R8	Supply conditions	°C; m3/h	per return distribution system (AHU fans, local fans, heating and cooling coils,	during operation	15 min	1 hour

				DSHP, PVT, PV, etc.)			
	R9	Return conditions	°C; m3/h	per supply distribution system (AHU fans, local fans, heating and cooling coils, DSHP, PVT, PV, etc.)	during operation	15 min	1 hour
	R10	Setpoint temperature	°C	per terminal unit (AHU, fancoil, air heaters, etc.)	during operation	15 min	1 hour
	R11	Zone Temperature	°C	per zone / microzone	during operation	15 min	1 hour
	R12	IEQ (CO2, PM2.5, VOCs, temperature, humidity, noise)	ppm; °C; %, dB	per zone / microzone	during operation	15 min	1 hour
	R13	Number Occupants	integer	per zone / microzone	during operation	15 min	1 hour
	R14	Distribution of Occupants	integer	per zone / microzone	during operation	15 min	1 hour
Decarbonisation as a service	R1	Appliances' consumption	W	per building	static	-	-
	R2	Type of building	text	per building	static	-	-
	R3	Location	longitude-latitude	per building	static	-	-
	R4	Building dimensions	m^2,m	per building	static	-	-
	R5	Bulding orientation	°	per building	static	-	-
	R6	Insulation type	text	per building	static	-	-
	R7	Type of windows	text	per building	static	-	-
	R8	Area of windows	m^2	per building	static	-	-
	R9	Central heating system's type	text	per building	static	-	-
	R10	Central heating system's capacity	kW	per building	static	-	-
	R11	Water heating system	text	per building	static	-	-
	R12	Water heating system's capacity	kW	per building	static	-	-
	R13	Available RES area	m^2	per building	static	-	-
	R14	Consumption	kWh	per building	from October 2023 to October 2024	-	-
	R15	Heating power	kWh	per building	from October 2023 to October 2024	-	-
Pan-EU Market Modelling (Artelys Crystal Super Grid)	R1	Heat consumption	kWh.th	per zone	Period installed or forecast	hourly	yearly
	R2	Heat source temperature of the heat pump	°C	per zone	Period installed or forecast	hourly	daily
	R3	Bivalent temperature of the heat pump	°C	per equipment	static	-	-

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	R4	Capacity of the heat pump	kW (el or th)	per equipment	static	-	-
	R5	COP of the heat pump	MW.th/MW.el as a function of °C	per equipment	static	expected COP as a function of heat source temperature	average COP
	R6	Backup heater efficiency	%	per equipment	static	-	-
	R7	Type of backup heater	No unit (gas or electricity)	per equipment	static	-	-
	R8	Thermal surface capacity (for PVT)	W/m^2	per equipment	static	-	-
	R9	PV surface capacity (for PVT)	W/m^2	per equipment	static	-	-
	R10	PVT surface (for PVT)	m^2	per equipment	static	-	-
	R11	Solar/electrical efficiency (for PVT)	%	per equipment	static	-	-
	R12	Solar/heat efficiency (for PVT)	%	per equipment	static	-	-
	R13	Heat storage technology (for heat storage)	-	per equipment	static	-	-
	R14	Heat storage capacity (for heat storage)	MWh	per equipment	static	-	-
	R15	Extraction power rating (Pmax_in) (for heat storage)	MW	per equipment	static	-	-
	R16	Injection power rating (Pmax_out) (for heat storage)	MW	per equipment	static	-	-
	R17	Discharge time (for heat storage)	h	per equipment	static	-	-
	R18	Energy Density (for heat storage)	kWh/m^3	per equipment	static	-	-
	R19	Input efficiency (for heat storage)	%	per equipment	static	-	-
	R20	Output efficiency (for heat storage)	%	per equipment	static	-	-
	R21	Loss rate (for heat storage)	%/h	per equipment	static	-	-
	R22	Storage T° range (for heat storage)	°C	per equipment	static	-	-
	R23	Energy storage capacity (for BESS)	MWh	per equipment	static	-	-
	R24	Extraction power rating (Pmax_in) (for BESS)	MW	per equipment	static	-	-
	R25	Injection power rating (Pmax_out) (for BESS)	MW	per equipment	static	-	-
	R26	Input efficiency (for BESS)	%	per equipment	static	-	-
	R27	Output efficiency (for BESS)	%	per equipment	static	-	-
	R28	Loss rate (for BESS)	%/h	per equipment	static	-	-

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	R29	CAPEX (for all technologies)	k€	per equipment	static	-	-
	R30	Annuel OPEX (for all technologies)	k€/yr	per equipment	static	-	-

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