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Digital Twin Architecture and Energy Management Strategies for Microgrid-Based Energy Communities

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ABSTRACT:

This research develops a conceptual design, software architecture, and rule-based control algorithms for a cloud-based digital twin system applied to a microgrid-based renewable energy community. Operating as a tertiary control layer, the proposed cloud-based platform is designed to support Level 5 autonomous operation within the digital twin maturity framework by enabling automated real-time data integration and system optimization.

The system mirrors the physical infrastructure of a seven-house microgrid within a multi-layered digital domain. Utilizing the C4 model abstraction framework, the software architecture defines interactions between core Community Sizing, Forecast, Market, and Energy Management System (EMS) platforms. Building Information Modeling (BIM) principles provide the visual foundation via Autodesk Revit, integrated seamlessly through the Autodesk Viewer. Functional data pipelines are mapped to circulate continuous sensor telemetry and external information across Apache Kafka, Spark, and Microsoft Azure cloud PaaS ecosystems.

The operational logic governing the energy community is executed via sequential Python-based algorithm flows. The UML abstraction framework is used to formalize operational states, process sequences, and execution conditions within the software architecture. Real-time rule-based dispatch strategies regulate self-consumption, surplus distribution, load supply, Battery Energy Storage System (BESS) management, and grid interactions, combined with day-ahead energy arbitrage planning. The system dynamically adjusts energy distribution flows in 15-minute time slots to correct discrepancies between forecasted and actual demand.

KEYWORDS: Digital Twin, Energy Management System (EMS), Renewable Energy Community (REC), Microgrid, Battery Energy Storage System (BESS), Rule-Based Energy Control, Energy Arbitrage, Building Information Modeling (BIM), Real-Time Telemetry

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1 Introduction

The current energy landscape is characterized by the ongoing energy crisis and the increasing global demand for electricity [1]. In response to growing demand and the Sustainable Development Goals (SDGs), there is a significant trend toward increasing flexibility, energy efficiency, and sustainability through the electrification of various systems [2]. This includes a transition from non-renewable energy sources, which are limited and produce greenhouse gas emissions, to renewable energy sources. To support a large-scale transition to renewable energy, a key requirement is the decentralization of the energy system [3]. Decentralization enables distributed generation and allows individual consumers to actively participate in the energy system.

Within this context, energy communities represent a viable solution, defined as groups of individuals who collectively produce, consume, and store energy from renewable sources [4].

Technological advancements enable the optimization of the development and management of energy communities. Advances in sensor technology, their integration into the Internet of Things (IoT), and increasing affordability simplify monitoring and improve awareness of system performance [5]. The availability of cloud computing and the analysis of big data enable forecasting and modeling of more complex energy systems [6]. At the same time, the development of microgrids and smart grids allows operation in islanded mode and bidirectional exchange with the central grid [3].

Collectively, these technologies enable the creation of a digital twin of an energy community that can operate partially or fully independently of the central grid. Such a system facilitates optimal sizing of power generators and battery energy storage systems, while also allowing the monitoring, visualization, and optimization of the energy system's operation.

1.1 Research Gap, Objectives, and Contributions

Recent literature on digital twin applications in energy systems highlights several limitations that remain evident in current research [9], [12], [19], [25], [35], [36]:

- Energy community operations, Local Energy Systems (LES), Building Information Modeling (BIM), IoT infrastructure, big data analytics, Energy Management Systems (EMS), and Battery Energy Storage Systems (BESS) are frequently investigated as separate research domains rather than as interconnected components of a unified energy ecosystem.
- Existing digital twin implementations predominantly focus on individual buildings, industrial facilities, or isolated energy assets. Consequently, limited attention has been devoted to community-scale digital twins capable of supporting the planning, operation, and expansion of renewable energy communities.
- Current studies commonly address specific stages of the energy community lifecycle, such as system design, monitoring, or operational optimization, without providing an integrated framework that supports the entire lifecycle from community establishment and infrastructure sizing to real-time management and future scalability.

Therefore, the literature reveals a gap in the development of an integrated digital twin framework capable of combining the planning, deployment, operation, and future expansion of renewable energy communities within a unified architecture. Such a framework should facilitate real-time monitoring, data-driven decision-making, energy flow optimization, and autonomous management while maintaining interoperability between physical infrastructure and digital services.

Accordingly, this thesis investigates how a cloud-based digital twin can integrate BIM, IoT, forecasting, market mechanisms, sizing, and EMS functionalities to support the lifecycle management of renewable energy communities.

To address this gap, the research proposes a lifecycle-oriented digital twin framework for renewable energy communities. The proposed framework integrates community establishment procedures, LES sizing, BIM-based digital modelling, IoT-enabled data acquisition, forecasting services, market functions, and EMS capabilities within a unified digital ecosystem.

The theoretical and technological foundation of the framework is built on the following domains:

- The energy community concept: Encompassing establishment prerequisites alongside operational and economic principles.
- The LES infrastructure: Focusing on system types, physical components, and required monitoring data.
- The digital twin framework: Evaluating technological potential, software development tools, and deployment environments.
- The BIM-based digital model: Defining specifications for the digital model and geometric Level of Detail (LOD) requirements.
- The IoT and data analytics infrastructure: Focusing on real-time data acquisition, transmission, cloud processing, storage, and analytics.

The architectural framework and operational logic are implemented through the following objectives:

- Proposing a digital twin architectural framework that mirrors the physical infrastructure of an energy community within a multi-layered digital domain.
- Establishing an energy system sizing framework based on net energy balance equations to optimize the capacity of PV panels and BESS.
- Designing a multi-level control hierarchy (primary, secondary, and tertiary) to separate strategic planning from microgrid stabilization.
- Developing a container-level software architecture defining interactions between core subsystems, including the Forecast, Market, and EMS platforms.
- Mapping functional data pipelines for real-time telemetry streaming and batch data processing using cloud PaaS ecosystems.
- Formulating rule-based real-time dispatch strategies (Surplus and Load) and predictive battery market strategies to optimize energy flows and improve economic performance.

1.2 Methodology and Thesis Structure

The research objectives were addressed through a multidisciplinary engineering methodology, combining methods of data architecture, software engineering, and power systems control.

- Energy System Analysis: Applied to evaluate the local energy context of Greece and structure the lifecycle boundaries of the energy community.
- Software Architecture Modeling: Utilized the C4 model abstraction framework (Context, Container, and Component levels) and BIM principles to systematically design the digital twin platform and its core internal subsystems (Forecast, Market, and EMS).
- Rule-Based Operational Modeling: Applied to develop the sequential execution algorithm of the EMS in Python, enabling solar energy allocation, P2P matching, and market-driven storage scheduling.
- State and Sequence Modeling: Implemented within the Unified Modeling Language (UML) framework to structure the execution of the algorithm and formalize the discrete operational states of individual houses and central BESS assets.

Based on this methodological approach, the thesis is structured into three main research chapters, framed by an introduction and a conclusion.

Chapter 2 (Theoretical Foundations) provides a comprehensive literature review of the foundational technologies enabling the digital twin.

Chapter 3 (Development Framework and Digital Twin Architecture) establishes the ICT architecture of the platform. Moving from macro-contextual factors to micro-level data exchanges, this section models the physical layout of a seven-house microgrid, maps the multi-level control hierarchy, defines the backend C4 container architecture, and details the functional data flows across Apache Kafka, Spark, and Microsoft Azure cloud ecosystems designed to support Level 5 autonomous operation.

Chapter 4 (Energy Management System Algorithms and Control Strategies) details the dynamic operational logic governing the energy community. It establishes the core energy flow principles and battery-based control mechanisms. This chapter formalizes the sequential execution logic of the EMS software via Python-based algorithm flows, models the discrete states of individual houses and battery energy storage systems, and evaluates the specific rule-based dispatch strategies alongside day-ahead battery market strategies for energy arbitrage.

2 Technologies for Digital Twin of the Energy Community

2.1 Energy Communities

Human economic activity involving the combustion of fossil fuels and the conversion of their chemical energy into electrical, thermal, and mechanical energy has led to significant environmental impacts and the depletion of non-renewable resources. Carbon dioxide (CO_2) and other greenhouse gases emitted during the combustion of oil, natural gas, and coal have intensified the greenhouse effect by increasing the absorption and re-emission of thermal radiation in the atmosphere, resulting in net energy accumulation within the Earth's climate system and, as a result, global warming.

One of the primary strategies to mitigate climate change is the large-scale electrification of economic sectors alongside the transition to renewable energy sources. In addition to eliminating direct greenhouse gas emissions, electricity produced from solar, wind, and hydropower enhances the overall efficiency of energy conversion processes while providing greater operational flexibility [2]. Geothermal energy and biomass, which do not increase net emissions when assessed over their full life cycle, exhibit high potential for conversion into thermal energy.

A critical component of this sustainable transition is the integration of distributed energy resources (DERs), which promotes collective participation in electricity generation, consumption, and supply. Under contemporary conditions, the traditional centralized power system architecture has demonstrated operational limitations, necessitating an evolution toward a decentralized and more resilient energy framework.

However, distributed generation, characterized by intermittency and variability, imposes additional stress on centralized power grids. It can cause network congestion during intervals of surplus generation and necessitates balancing or ancillary services during periods of insufficient output [7]. These dynamics complicate the maintenance of voltage stability, frequency regulation, and phase synchronization, while also reducing system inertia.

A viable response to the challenges associated with the large-scale integration of DERs is the establishment of energy communities focused on renewable energy production, local self-consumption, transmission loss reduction, and grid stability support. These communities enhance system resilience, facilitate demand-side management, and contribute directly to the decarbonization of the energy sector.

2.1.1 Operational Principles

The principal components of an energy community are DERs, which may include solar photovoltaic (PV) or thermal panels, wind turbines, biomass-based electricity generators or thermal systems, geothermal heat pumps, and gas-fired generation units. In urban environments, due to high building density, the most common method of energy generation is the use of rooftop solar PV installations [8].

Energy communities are classified into two types [9]:

- Local Energy Communities (LECs): Communities oriented toward local energy production and consumption to reduce the load on the central grid. They can include both renewable and non-renewable sources; for instance, gas-fired units may be employed as a backup system during periods when internal production cannot meet the community's demand.
- Renewable Energy Communities (RECs): Communities whose primary objective is the production and consumption of electricity exclusively from renewable energy sources, strictly excluding the use of fossil-based sources.

A strategic element in optimizing energy community operation is the deployment of Battery Energy Storage Systems (BESS), which allow energy to be accumulated during periods of surplus generation and utilized when consumption exceeds production [10].

Some energy community frameworks permit energy arbitrage. It involves storing electricity from the centralized grid during periods of low demand and low prices, with subsequent sale back to the grid during periods of high demand and high prices. The remuneration for electricity supplied to the centralized grid can be fixed, dynamic (market-driven), or mixed, depending on local regulations.

2.1.2 Economic Models

Since energy communities involve the participation of multiple stakeholders, including citizens, businesses, and public or private institutions, an essential element of their operation is the organization of internal economic relations. Two widely adopted approaches to energy exchange and the structuring of economic relations between community members and the centralized grid are distinguished [9]:

- Collective Self-Consumption (CSC): This model is oriented toward maximizing the benefits of local energy utilization. Within this framework, all generated energy is supplied to the centralized power system and subsequently allocated among participants. Each member is entitled to consume an amount proportional to their investment share, and any deficit is purchased at the prevailing market price. During intervals of surplus generation, energy can be sold to the grid or stored in a BESS. In contrast to energy allocation based on percentage ownership, storage system distribution focuses on financial benefits proportional to the investments made, determined by the total savings achieved through storage utilization. The charging and discharging strategy is established by the community to maximize overall financial efficiency, while energy consumption at the moment of generation or from storage is incentivized through additional remuneration.
- Peer-to-Peer Model (P2P): This approach is designed to enable direct energy trading within the community, where surplus energy produced by individual participants is sold to other members at internally agreed prices. A dedicated P2P platform and blockchain technology are utilized to ensure secure transactions and settlements. Although this model requires a more complex digital infrastructure, it generally offers more favorable financial conditions for energy trading between community members.

2.1.3 Application Potential

The greatest prospects and the strongest need for establishing energy communities and LES as their infrastructure arise in the following cases:

- Remote and Isolated Areas: This includes regions located at a distance from the central power grid, such as suburban areas, islands, and hard-to-access locations. The key condition for successful implementation is the installation of a sufficient number of generation units, a backup system, and battery capacity to meet local electricity demand, thereby ensuring the community’s energy independence and enabling the microgrid to operate in islanded mode [4], [12].

- Disaster-Prone Regions: This encompasses areas exposed to natural disasters that threaten the integrity of the central power system and cause disruptions in the electricity supply. In remote locations where fault repair may take longer, resulting in extended outages, the establishment of energy communities becomes particularly important [11].
- Urban Environments: This involves cities seeking to support the energy transition, reduce dependence on centralized supply, and mitigate exposure to market price volatility. Under a bottom-up approach, where the aggregation of buildings into an energy community is based on the complementarity of generation potential and consumption profiles, economic benefits and investment returns become more predictable [8].

By enabling coordinated local generation, storage, and exchange of renewable energy, energy communities represent a practical and scalable pathway toward a more efficient and decentralized energy system.

2.2 Local Energy Systems

The primary structural manifestation of such a decentralized system is the community microgrid. This microgrid connects the elements of the LES and the members of the energy community, forming a coordinated infrastructure capable of operating in islanded mode when local generation is sufficient to satisfy the community’s electricity demand. Although the establishment of an energy community does not require the deployment of a microgrid, its implementation reduces the load on the centralized grid, enhances operational autonomy, and enables more effective energy management by treating the community as an independent system [8].

The need for microgrid establishment is particularly significant in the P2P model, where direct energy exchange between members relies on local infrastructure. In contrast, the CSC model can be integrated into the centralized grid with relatively low complexity and monitored through conventional metering of generation, consumption, and energy sales.

To enable the benefits of local generation, energy communities can adopt different LES configurations that support varying scales of renewable energy production and degrees of independence from the centralized power system [11]:

- Individual energy systems: Systems equipped with solar photovoltaic installations and battery storage for single-family houses.
- Nanoscale grids: Networks uniting 5–10 community members who operate individual systems (single-family houses) or share rooftop installations in a multi-apartment building.
- Microgrids: Systems integrating a larger number of participants at the level of several buildings, districts, or villages.

2.2.1 Electricity Generation Systems

To satisfy the electricity demand within a local network, various primary energy inputs must be harnessed. Depending on geographical and infrastructural factors, the following energy sources are utilized for electricity generation [10]:

- Solar energy refers to the conversion of energy generated by nuclear fusion in the Sun and transmitted in the form of electromagnetic radiation (photons) into thermal energy using solar collectors or into electricity using photovoltaic panels.
- Wind energy involves the conversion of the kinetic energy of wind into electricity. The primary source of the wind's kinetic energy is solar thermal energy, which heats the Earth's surface and subsequently warms the atmospheric air layers. Wind movement results from the uneven heating of atmospheric air layers and pressure differences caused by gravitational effects: warmer, lighter air masses tend to rise above the Earth's surface, whereas cooler, denser air masses descend closer to it.
- Hydropower represents the conversion of the kinetic energy of water into electricity. The primary source of this energy is solar radiation, which drives the hydrological cycle through evaporation and precipitation, while gravitational

force enables water to flow from higher to lower elevations, converting potential energy into kinetic energy.

- Bioenergy involves the conversion of chemical energy stored in organic compounds into thermal energy or electricity. This chemical energy is accumulated through photosynthesis, during which plants convert solar radiation into biomass. The organic materials used include woody biomass, agricultural residues, livestock waste, food waste, and landfill gas.
- Geothermal energy refers to the utilization of the Earth's thermal energy, which arises from radioactive decay and residual heat from the planet's formation. It can be used as heat or converted into electricity. Geothermal resources can be utilized at the level of shallow geothermal systems as well as deep geothermal systems.

PV installations represent the most common method of renewable energy generation in urban environments [8].

The electrical energy generated by photovoltaic systems can be estimated using the following equation:

$$E_{gen} = G * S * t * \eta$$

Where E_{gen} represents the total electricity generated by solar energy (kWh), G is the total solar irradiance (kW/m²), S is the surface area of the solar panels (m²), t is the duration of illumination (h), and η is the solar panel efficiency (-), typically ranging between 15–25% depending on the PV technology. This simplified equation assumes constant irradiance and efficiency during the analyzed period and neglects temperature effects, shading, inverter losses, and panel degradation.

Within this framework, the total solar irradiance (G) consists of direct, diffuse, and reflected components. Direct radiation provides the highest energy input and therefore contributes most significantly to electricity generation under clear-sky conditions. Diffuse radiation enables continued energy production during periods of cloud cover, although with reduced output. Reflected radiation originates from surrounding surfaces and can increase total energy generation for bifacial photovoltaic panels, where the additional contribution can reach 5–15% depending on surface albedo.

2.2.2 Battery Energy Storage Systems

Due to the stochastic and intermittent nature of renewable sources, particularly solar radiation, generation profiles often do not align with consumer demand. To mitigate these temporal mismatches, specialized buffering infrastructure is required. A key component of a LES that extends its independence beyond active generation periods is the BESS, which enables energy accumulation and load shifting [7], [10].

The operational roles of BESS can be categorized as follows:

- Full Microgrid Autonomy: BESS completely eliminates reliance on the centralized power grid by providing sufficient storage capacity to satisfy total electricity demand.
- Mitigated Grid Dependence: BESS covers electricity demand during peak load periods and partially interacts with the centralized grid for charging and balancing during intervals of insufficient local generation.

Temporal scales of application include:

- Short-term (1-3 days): Smoothing the mismatch between power generation and consumption over a multi-day horizon.
- Seasonal: Balancing long-term variations in generation and load profiles across different seasons.

Therefore, BESS capacity requirements scale according to whether the primary objective is daily load smoothing or seasonal balancing.

2.2.3 Energy System Infrastructure and Control

Translating these operational storage roles into a functioning system demands an electrical infrastructure capable of managing distinct, multi-directional power flows. Electricity is supplied through a distribution system consisting of direct current (DC) and alternating current (AC) buses. Solar panels and BESS operate on DC, whereas conventional electrical appliances operate on AC [7]. Power inverters are utilized to convert current between the two types. Grid-following inverters correspond to the lowest level (Primary Control) of power system management.

When a microgrid operates in islanded mode, a power inverter capable of establishing a voltage waveform and synchronizing all voltage sources is required. Grid-forming inverters correspond to the intermediate level (Secondary Control) of power system management.

The upper level (Tertiary Control) of energy system control is represented by the Energy Management System (EMS), which is responsible for the strategic and economic optimization of the energy system [3]. The logic of energy community management is defined within the EMS.

An essential part of the microgrid energy infrastructure is the Point of Common Coupling (PCC), which acts as the switching point between grid-connected and islanded modes of operation.

2.3 Digital Twin Technology

The practical implementation of such decentralized energy systems requires an integrated technical architecture, which is effectively realized through digital twin technology. Throughout the system's lifecycle, this virtual framework supports all stages from demand-based planning to real-time sensor monitoring, P2P/CSC financial tracking, and autonomous EMS control.

The concept of digital twins was introduced by Michael Grieves. According to this concept, a digital twin consists of three main components: a physical object in the real world, a virtual representation in the digital space, and data integration that links the physical and virtual environments [16].

Thus, a digital twin is a virtual representation that possesses the properties of the physical object and enables the study of the object’s behavior in a virtual environment under varying internal and external conditions. A digital twin is directly connected to real-time data from the object, which allows the twin to reflect the current state of the physical system. The result of data integration into a digital twin is analysis and visualization that support data-driven decision-making [17].

During the Apollo program, NASA was among the first to apply principles similar to the digital twin concept, such as simulating telemetry data received from a real object and predicting its behavior. However, these principles differed from the actual digital twin concept due to the absence of continuous automated data integration between the physical object and the digital model [18].

Digital twins are widely used to reduce development costs by identifying errors at the design stage, reducing the number of physical prototypes, and analyzing system behavior under extreme conditions. During the operation phase, they are used to optimize resource usage and predict maintenance needs, even when direct access to the physical object is not available.

2.3.1 Architectural Types and Maturity Levels

The following levels of integration between the digital object and the physical system can be identified. The connectivity can increase over the object's lifecycle [19]:

- Digital model: A digital representation of a designed or existing object that does not support automatic data exchange between the physical system and the digital model. It is primarily used during the design stage for simulation and optimization in the absence of real data.
- Digital shadow: A digital model of a physical object with a one-way data connection. All changes occurring in the physical world are automatically integrated and reflected in the digital model. It is typically applied during the production stage when sensor data is added to represent the real state of the object.
- Digital twin: A digital model with a two-way data connection to the physical object. Information about the real object is integrated and analyzed in the digital environment. Decisions made based on this data and implemented in the digital twin result in changes in the physical system. It is actively used during the operation phase to support informed decision-making and corresponding system adjustments.

Digital twins are further classified based on maturity levels, which define their functional capabilities [20]:

- Level 0 (No twin): The digital model does not provide autonomous data integration from the physical object.

- Level 1 (Descriptive): The model collects data and reflects the state of the physical object in real-time.
- Level 2 (Informative): The model includes historical data and can analyze current data in relation to past states.
- Level 3 (Predictive): The twin is capable of forecasting the future state of the object using machine learning or physical models.
- Level 4 (Optimizing): The twin enables the simulation of different system behavior scenarios and supports the selection of an optimal solution.
- Level 5 (Autonomous): The digital twin can autonomously implement changes to the physical system to maintain optimal operation.

2.3.2 Development Environments and Core Tools

Implementing a digital twin for an energy community requires a cohesive technical framework. To develop the framework according to current industry standards, the capabilities of leading enterprise ecosystems must be analyzed based on their lifecycle coverage, data processing constraints, and domain-specific applications.

2.3.2.1 Microsoft Azure Cloud Ecosystem

Microsoft provides a suite of cloud-based tools that are extensively used for digital twin development. It is one of the leading providers of cloud computing solutions and offers a wide range of tools for big data processing [21], [41].

The platform links physical IoT telemetry to virtual representations of system assets. Data from edge devices is routed through Azure IoT Hub into Azure Digital Twins (ADT), which serves as the central spatial graph of the system. Azure Functions execute the operational and control logic and transmit control signals back to the physical infrastructure. For end users, Power BI provides analytical dashboards, while 3D Scenes Studio delivers interactive 3D visualization.

2.3.2.2 Siemens Xcelerator and Industry 4.0 Platform

In the industrial domain, the Siemens Xcelerator ecosystem is one of the leading platforms for digital twin development and sets industry standards in this field. It divides the digital twin across three lifecycle stages: product design, production simulation, and operation, enabling monitoring, optimization, and improvement of future product iterations [22].

Siemens is widely recognized as a key driver of the Industry 4.0 concept, which focuses on automated and flexible production aimed at meeting individual customer needs. One of the main tools in this concept is the utilization of digital twins in industrial processes. Simulation within a digital twin environment enables the identification of errors before production, reducing costs and the number of prototypes. This is achieved through the integration of sensors into an Industrial Internet of Things (IIoT) network, collecting large volumes of data, and processing this data using cloud computing technologies. The processed data is used by artificial intelligence for predicting maintenance needs, optimizing operations, and controlling production systems, where robots and 3D printing technologies serve as execution mechanisms [23].

In terms of functional architecture, the design and simulation stages are executed using engineering tools like NX and Simcenter. For the operational phase, the ecosystem shifts to pre-configured cloud platforms: Insights Hub connects physical assets with sensor data, while Building X and Electrification X serve as specialized, standalone environments for building and smart energy network management, utilizing Mendix to build custom control web applications.

2.3.2.3 Autodesk BIM and Smart Buildings Solutions

Autodesk is a company that established the BIM standard in architecture and construction [24]. A BIM object is the basis for a building digital twin [25]. In addition to tools for digital model development, the company also offers tools for integrating data into them [26]. The primary focus of the company is at the building scale.

A Building Management System (BMS) is another key term in this domain that defines a system for building monitoring and control using sensors and controllers. It supports both wired and cloud-based data transmission from devices. When a BMS is integrated into a BIM digital model, it forms a digital twin of a building, which is controlled by a smart building algorithm to improve efficiency and safety.

BIM (Digital Model) + BMS (IoT) → Building Digital Twin → Smart Building (+ Algorithms)

The functional logic of this ecosystem centers on parametric architectural design and lightweight web visualization. Detailed physical geometry and macro-level urban layouts are developed using Autodesk Revit, Civil 3D, and InfraWorks. For real-time data integration, Autodesk Tandem serves as the platform that injects IoT sensor telemetry directly into the digital model. The final presentation layer relies on Autodesk Viewer to render 2D and 3D models natively in a web browser. Since the Autodesk infrastructure is not designed for big data processing, its primary value is as a flexible visualization interface that displays data processing results generated by external cloud platforms.

2.3.2.4 ArcGIS CIM and Smart City Tools

ArcGIS is a platform used for designing and managing objects at the city scale. Its primary advantage is the utilization of Geographic Information System (GIS) technology, which represents a geospatial database and provides accurate spatial context.

It is a powerful tool for City Information Modelling (CIM), a technology that extends BIM to a larger scale by integrating BIM and GIS [27]. A CIM object is a digital model used for creating a digital twin of a city, which serves as the basis for smart city algorithms [28].

A city digital twin can be considered a model that describes relationships between urban variables as well as their current values. This model is used by smart city algorithms for simulation, optimization, and city management [29].

BIM (Digital Model) → CIM (+ GIS) → City Digital Twin (+ IoT data) → Smart City (+ Algorithms)

The ArcGIS ecosystem provides one of the most effective solutions for creating CIM objects and digital twins of cities when the goal is visualization and information management [30].

ArcGIS Pro and ArcGIS CityEngine are used to model and analyze existing urban environments and complex 3D structures. ArcGIS GeoBIM connects ArcGIS and Autodesk platforms, enabling the integration of individual BIM objects. ArcGIS Reality generates high-precision 3D Reality Mesh models from drone imagery. For real-time operations, ArcGIS Velocity and ArcGIS GeoEvent Server ingest and process IoT telemetry. ArcGIS Insights supports dashboarding, while ArcGIS Experience Builder is used to deploy customized digital twin applications.

2.3.2.5 Bentley Systems Engineering Environment

Bentley Systems is a widely recognized ecosystem for designing and managing digital twins of infrastructure at the city scale, with a strong focus on engineering accuracy rather than spatial accuracy. It can be considered a standard for engineering-oriented CIM and city digital twin [31].

In terms of functional architecture, the baseline 2D and 3D geometries, architectural models, and utility networks are generated using design tools like MicroStation, OpenBuildings Designer, OpenRoads, OpenUtilities, and OpenCities. For data integration and cloud storage, the ecosystem relies on iTwin Hub and the iModel database. During the operational phase, iTwin IoT receives physical sensor telemetry and streams it into the presentation layer. The final virtual interaction is managed within iTwin Experience and iTwin Viewer, which display the twin natively on custom web platforms for analysis, utilizing LumenRT for realistic geometric rendering.

2.3.2.6 Game Engines and Immersive Visualization

Game engines such as Unreal Engine and Unity address the need for real-time rendering of interactive and photorealistic models. They can be used for visualizing digital models and digital twins with real-time sensor data. Game engines enhance models with animation and interactivity.

Unreal Engine is comparatively more specialized in architecture and construction, while Unity is used for the visualization of industrial systems. Unreal Engine provides a more realistic rendering of complex geometry compared to Unity, but requires higher computational resources. As a result, performance on mid-range hardware is typically smoother and faster in Unity [32], [33].

Additionally, these engines can be utilized to develop digital-twin-based applications, including fully interactive Virtual Reality (VR) environments, Augmented Reality (AR) data overlays onto the physical world, and shared Metaverse spaces.

2.3.3 Ecosystem Synthesis and Architectural Strategy

The evaluated ecosystems exhibit distinct strengths depending on the application domain. Autodesk and Bentley support BIM-based infrastructure representation, while ArcGIS provides geospatial integration. Siemens Xcelerator focuses on industrial automation, whereas Microsoft Azure offers a comprehensive cloud-native environment for IoT integration, real-time analytics, and autonomous control services.

Siemens Xcelerator served as a reference framework demonstrating the application of digital twin technology throughout the entire lifecycle of an energy system. In parallel, the Smart Building and Smart City concepts helped position the energy community at an intermediate territorial scale between individual buildings and urban energy systems. This perspective enables both downward integration with BMS and upward integration with CIM to support energy management across larger urban districts.

All reviewed ecosystems demonstrate a similar sequential progression in digital twin development. Initially, a digital model of the system assets is constructed. Subsequently, these model elements are mapped to physical sensors that transmit telemetry data. Following this, the analytic, visualization, and decision-making logic is defined to enable autonomous operations. The final stage entails rendering the digital twin within a user interface. While each ecosystem includes native visualization utilities, gaming engines can be integrated for advanced rendering.

Data ingestion, processing, and transmission utilities, such as Azure IoT Hub or iTwin IoT, are engineered to sustain robust system operations across thousands of IoT sensors. Data integration platforms like Azure Digital Twins or Autodesk Tandem focus heavily on asset monitoring and event response rather than the execution of complex computational logic. The framework developed in this study represents an algorithm-first digital twin with scalable IoT stream ingestion capabilities. Given the comparatively limited scale of the proposed seven-house energy community, the deployment of dedicated enterprise digital twin platforms is not considered essential. Instead, the architecture relies on a lightweight combination of cloud services, data-processing tools, and BIM-based visualization components tailored to the requirements of the proposed application.

Rather than adopting a singular monolithic ecosystem, the architecture synthesizes distinct tools from various platforms. Therefore, the proposed architecture in this thesis adopts a BIM-centered approach based on Autodesk technologies for physical system representation and visualization, while utilizing Microsoft Azure as the primary cloud platform for data processing, analysis, and storage. Furthermore, it handles the logic calculation and digital twin synchronization.

2.4 Building Information Modeling

Following the analysis of the software platforms and cloud ecosystems, the actual implementation of the digital twin begins with establishing its geometric foundation using BIM.

In 2002, Autodesk introduced the concept of BIM, which is an approach to design, construct, and manage buildings that provides project information in an integrated and coordinated environment [24]. It can be implemented using CAD technology, object-based CAD as an extension of conventional CAD, and Parametric Building Modelling.

When changes are introduced into a project, all related dependencies are automatically updated. As a result, BIM reduces development time, minimizes errors, and consequently lowers project costs.

BIM consists of seven dimensions: three-dimensional space (3D), scheduling (4D), cost (5D), sustainability (6D), and operation/maintenance (7D), which together cover all stages of the building lifecycle. Therefore, BIM is often considered a data management process within a unified model throughout the entire project duration, serving as a platform for collaboration among all stakeholders [25].

Among all technologies supporting the BIM approach, Parametric Building Modelling provides the highest level of flexibility and functionality. This technology combines model geometry with information about object behavior, enabling simulation of building performance in real physical conditions. Therefore, a BIM model created using Parametric Building Modelling can be considered a digital model of a building. This technology is commonly implemented using Autodesk Revit.

In addition to architectural and structural design, Revit supports the integration of information about engineering systems, including HVAC, electrical systems, and water supply. For the energy community project, the digital model should include detailed 3D information on building architecture and electrical systems.

2.4.1 Geometric Levels of Development

In the BIM context, LODs indicate the scope of detail and the reliability of information in the model [34]:

- LOD 100 (Conceptual design): Elements are represented as a general shape, allowing the estimation of building area, volume, and orientation.
- LOD 200 (Schematic design): Elements have approximate dimensions, shape, and location, representing the overall design and structure of the object.
- LOD 300 (Detailed design): Geometry is accurate in shape, size, and position, but engineering systems are not interconnected; used for producing primary drawings.
- LOD 350 (Construction documentation): The model includes information about interactions between engineering systems; used for generating construction documents.
- LOD 400 (Fabrication and assembly): The model contains detailed information required for construction and installation.
- LOD 500 (As-built): A digital representation of the physical building with accurate information about its actual post-construction state.

The development of a digital twin from a digital model requires accurate information about the actual building state, corresponding to LOD 500. However, for planning energy communities at the design or construction stage, LOD 350 or LOD 400 can be sufficient.

2.5 IoT and Data Analytics Infrastructure

While BIM provides the spatial and structural foundation, the transformation of a static digital model into a dynamic digital twin requires a continuous transmission of real-time operational data. This data integration is enabled by the IoT.

As an evolutionary extension of the global Internet, which historically interconnected people and information, the IoT paradigm establishes a network that interconnects numerous physical devices. Devices within this network generate, process, and exchange data among themselves, or transmit it to other systems via the Internet [39].

The architecture of IoT systems can be structured into five layers [5]:

1. Perception layer: Facilitates interaction between digital devices and the real world, where sensors collect environmental data contributing to big data generation.
2. Transport layer: Enables data transmission between devices and the processing system using communication protocols.
3. Processing layer: Facilitates data processing through cloud, edge, or fog computing infrastructures.
4. Application layer: Supports the practical utilization of data, visualization, and data-driven system management.
5. Business layer: Responsible for user privacy, strategic decision-making, and business models.

In the context of a digital twin for an energy community, these layers collectively establish the technical infrastructure required to acquire, transmit, process, and utilize operational data for monitoring, forecasting, and energy management.

2.5.1 Sensors and Data Acquisition

The data acquisition infrastructure, corresponding to the perception layer of the IoT architecture, provides the interface between the physical energy system and its digital representation. This infrastructural layer primarily consists of hardware sensors, actuators, and smart IoT devices.

Sensors measure physical parameters, while actuators initiate actions that modify environmental conditions. Modern IoT devices combine sensing capabilities with local computing and communication functions through embedded microcontrollers and wireless transmitters [23]. This integration improves reliability and enables autonomous operation at the edge of the network.

IoT devices connect to the Internet either directly through IP-based communication or indirectly via gateways. The unique IP address enables bidirectional communication, allowing external systems to transmit commands back to field devices when required.

Sensors are commonly classified as contact or remote sensing devices. Contact sensors require direct interaction with the measured object, whereas remote sensors acquire information through electromagnetic radiation. Remote sensors may operate passively by detecting naturally emitted radiation or actively by generating and receiving reflected signals [39].

After data acquisition, measurements are transferred to a microcontroller, which structures the information according to the selected application protocol. The radio transmitter then converts the digital message into electromagnetic signals for wireless transmission according to the network protocol.

At the receiving side, a modem or receiver demodulates the signal and reconstructs the original message. The data is then forwarded to a gateway, which encapsulates the information into IP packets and transmits it through the Internet to cloud services or messaging platforms.

In broker-based architectures such as MQTT, the gateway forwards messages to a broker that manages authorization, topic routing, and message distribution. If active subscribers exist, the broker delivers the message to the corresponding applications. Alternatively, protocols such as HTTP or CoAP typically transmit data directly to the target application without intermediary brokers.

2.5.2 Communication Protocols

The transport layer is responsible for delivering information collected by the perception layer to processing and application services. This communication relies on application and network protocols that define message formatting and transmission mechanisms.

At the application layer, IoT systems commonly utilize the following protocols [39]:

- MQTT (Message Queuing Telemetry Transport): Widely used protocol for IoT devices. It is energy-efficient and performs reliably under unstable network conditions. However, it requires a persistent connection to a broker.
- CoAP (Constrained Application Protocol): A lightweight protocol conceptually similar to HTTP. It supports fast exchange of short messages during device activation periods. When the device is inactive, it is unable to receive messages.
- HTTP/REST: A widely adopted protocol of the Internet. It requires comparatively higher computing power and energy resources.

While application protocols define message structures, network protocols determine how information is physically transmitted. Their selection typically involves a trade-off between communication range, data rate, and energy consumption [5].

For short-range communication, technologies such as Wi-Fi and Bluetooth Low Energy (BLE) provide connectivity within buildings and local networks. Smart home and building automation systems frequently employ Zigbee or Z-Wave due to their mesh-network capabilities and low power requirements. Industrial environments often utilize WirelessHART to achieve reliable communication among distributed devices [23].

For long-range deployments, Low-Power Wide-Area Network (LPWAN) technologies such as LoRaWAN and NB-IoT enable communication over several kilometers while maintaining low energy consumption. In energy systems, Power Line Communication (PLC) may also be utilized by transmitting data directly through existing electrical infrastructure [7].

After data reaches the cloud environment, an additional messaging layer is often required to decouple data producers from downstream processing services. In large-scale IoT systems, distributed event-streaming platforms such as Apache Kafka are frequently utilized for this purpose. Unlike MQTT brokers, which primarily facilitate device-to-application communication, Kafka is designed for high-throughput data ingestion, persistent event storage, and scalable distribution of data streams across multiple consumers [43].

The selection of communication protocols depends on the operational requirements of the digital twin. Energy community applications typically prioritize reliable telemetry transmission, low energy consumption, seamless integration with cloud-based analytics platforms, and scalability. As a result, practical digital twin implementations often adopt a layered communication architecture in which PLC with MQTT is utilized for sensor-level telemetry transmission, while Apache Kafka serves as the backbone for cloud-based event streaming and communication between analytical and control services.

2.5.3 Cloud-Based Big Data Processing

The continuous transmission of telemetry packets through IoT communication networks results in the accumulation of large volumes of heterogeneous operational data. To process this multi-source data stream and support data-driven decision-making, the system integrates big data analytics and cloud computing technologies.

The core characteristics of big data are defined through the 5V concept [5], which encompasses volume, velocity, variety, value, and veracity. Within an energy community, this translates to the real-time transmission of large-scale, heterogeneous sensor datasets that undergo filtering and validation to extract actionable knowledge for decision-making.

In the context of a digital twin for an energy community, the collected information includes structured sensor measurements, semi-structured metadata records, and external datasets such as generation and consumption forecasts and electricity market prices. Therefore, a scalable processing infrastructure is required.

Cloud computing provides on-demand access to computational resources, storage, and networking services while ensuring scalability, fault tolerance, and high availability [40]. Since the proposed digital twin is implemented on Microsoft Azure, the Platform-as-a-Service (PaaS) model is particularly relevant because it enables application deployment without direct management of underlying infrastructure [41].

To further reduce latency, data processing can be distributed between cloud and local resources. Edge computing performs selected computations directly on data-generating devices, while fog computing introduces an intermediate processing layer within the local network before data is transferred to the cloud [23].

Big data processing can be performed either in batch mode or in real-time. Batch processing accumulates large volumes of historical data before execution and is suitable for forecasting and long-term optimization tasks. Real-time processing analyzes incoming streams immediately upon arrival and supports operational control functions [43].

To achieve scalable processing, distributed computing frameworks are commonly employed. Apache Spark performs parallel and distributed processing by decomposing datasets across multiple nodes while utilizing in-memory computation to reduce latency.

The processed information can be stored for future operational analysis. Relational databases maintain consistent, structured records, while NoSQL databases scale to accommodate unstructured or semi-structured datasets generated by IoT systems [40].

2.5.4 Analytics and Decision Support

Once data has been acquired and processed, it becomes available for analytical evaluation and operational decision-making. Depending on the application requirements, data can be analyzed directly from real-time streams or retrieved from persistent storage for historical and predictive analyses. These functions correspond to the application and business layers of the IoT architecture, where data is transformed into actionable knowledge for energy community management.

Different analytical approaches can transform processed data into actionable information [40]:

- Qualitative analysis: Provides descriptive interpretations of historical events.
- Quantitative analysis: Represents system behavior through numerical indicators.
- Statistical methods: Include correlation analysis, regression techniques, and A/B testing, which can be utilized to identify relationships between variables and evaluate system performance.
- Machine Learning (ML) algorithms: Include supervised learning for forecasting, unsupervised learning for segmentation and anomaly detection, and reinforcement learning for the development of optimal control policies [5].
- Graphical analysis and data visualization techniques: Utilize dashboards, time-series plots, heat maps, network graphs, and spatial representations to facilitate human interpretation of system performance.

Within the digital twin framework proposed in this research, data analytics is primarily performed within the EMS. Operating at the application layer, the EMS evaluates incoming operational telemetry to optimize energy flows. Forecasting services can utilize ML models trained on historical energy data to estimate future system behavior. The analytical outputs generated by the EMS and forecasting services are presented to community members through graphical visualization tools and operational dashboards, improving transparency and awareness of system performance.

The application layer of the digital twin provides the operational intelligence required to execute tertiary-level energy management and optimization. The business layer, in turn, utilizes analytical outcomes to support long-term strategic decision-making at the community level. This includes the evaluation of economic performance, optimization of tariff structures, and assessment of system expansion and investment scenarios.

3 Development Framework and Digital Twin Architecture for Energy Communities

3.1 Local Energy Context

The establishment of an energy community is initiated with a contextual analysis of the local energy context. Taking Greece as a case study for community formation, an evaluation was conducted regarding electricity prices, solar generation profiles, and consumption patterns. Figure 1, Figure 2, and Figure 3 illustrate characteristic patterns for representative winter and summer days, utilizing data sourced from the ENTSO-E Transparency Platform.

The diagrams clearly demonstrate the following dynamics:

- The peak of solar generation coincides with the minimum electricity price, whereas the peak of electricity prices occurs after solar generation ceases.
- The peak in energy consumption in summer correlates with maximum energy generation and is driven by cooling requirements.
- The peak of consumption in winter occurs after generation ceases and is associated with heating requirements.
- Solar generation in summer exceeds generation in winter, yet energy consumption in summer exceeds winter consumption to a greater extent.
- Electricity prices in winter are higher than electricity prices in summer.

These observations demonstrate that the integration of BESS represents an efficient and economically viable solution to mitigate peak electricity prices. The substantial increase in summer energy consumption is not fully compensated by the corresponding rise in solar generation. Dimensioning the system to fully cover summer demand can result in generation surpluses during the winter. Nevertheless, the monetization of this winter surplus by exporting electricity to the grid during periods of peak prices can accelerate the payback period and enhance the overall financial viability of the system.

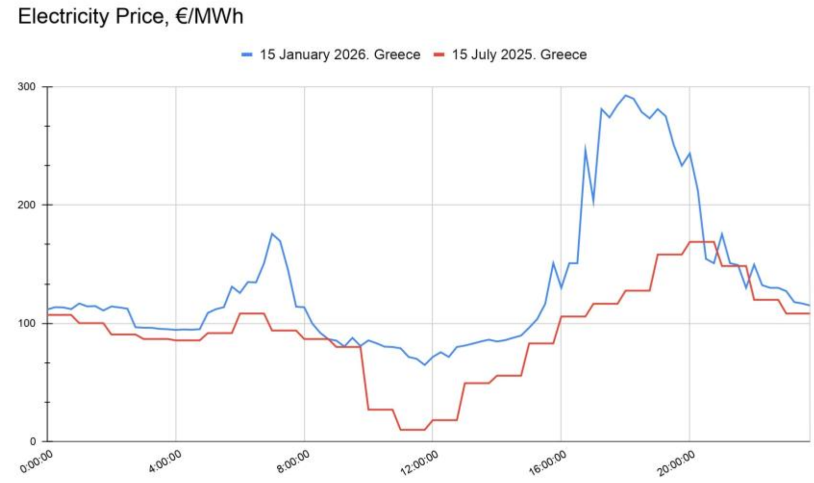

Figure 1. Electricity Price Chart

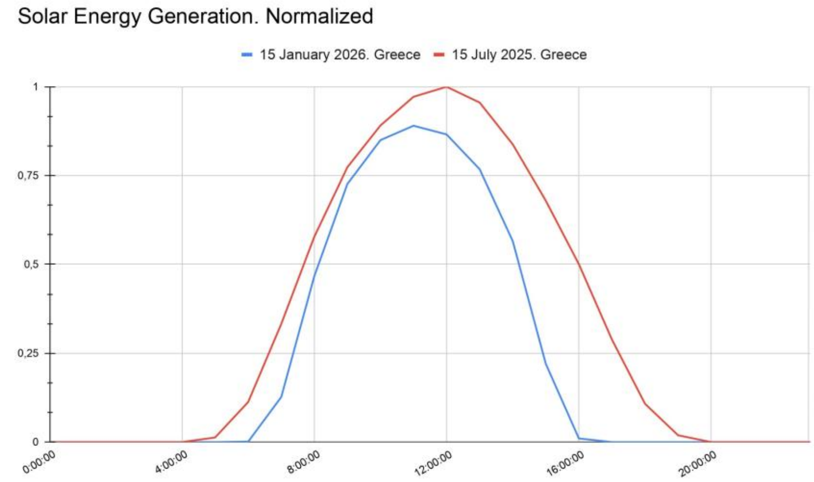

Figure 2. Solar Energy Generation Chart

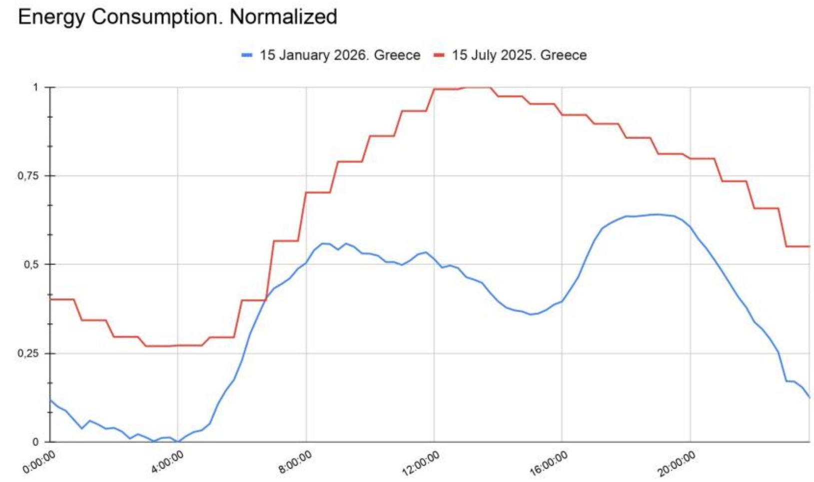

Figure 3. Energy Consumption Chart

3.2 Microgrid Physical Layout

Based on the constraints and dynamics identified in the contextual analysis, a specific physical infrastructure must be defined. To serve as the visual foundation for the digital twin, a digital model of a residential complex comprising seven single-family houses was adopted. Figure 5 illustrates the ground floor plan of the private complex, while Figure 6 presents the energy community roof plan.

These households were aggregated into a renewable energy community interconnected by a microgrid designed to enable autonomous operation. Each residential unit is equipped with rooftop PV panels and an inverter to convert DC into AC. Additionally, an electricity meter is installed at each household to monitor the bidirectional energy flows, indicating the volume of energy consumed from and fed into the community network.

The energy community utilizes a shared BESS coupled with a DC-to-AC inverter. A primary electricity meter is deployed to record the total energy flows entering and exiting the microgrid infrastructure after the PCC. Figure 4 details the architecture of the LES.

Distributing the capital cost of the energy system among community members significantly reduces the initial investment required from an individual participant. Furthermore, a shared BESS facilitates economies of scale, thereby reducing the unit cost of stored energy as the BESS capacity increases.

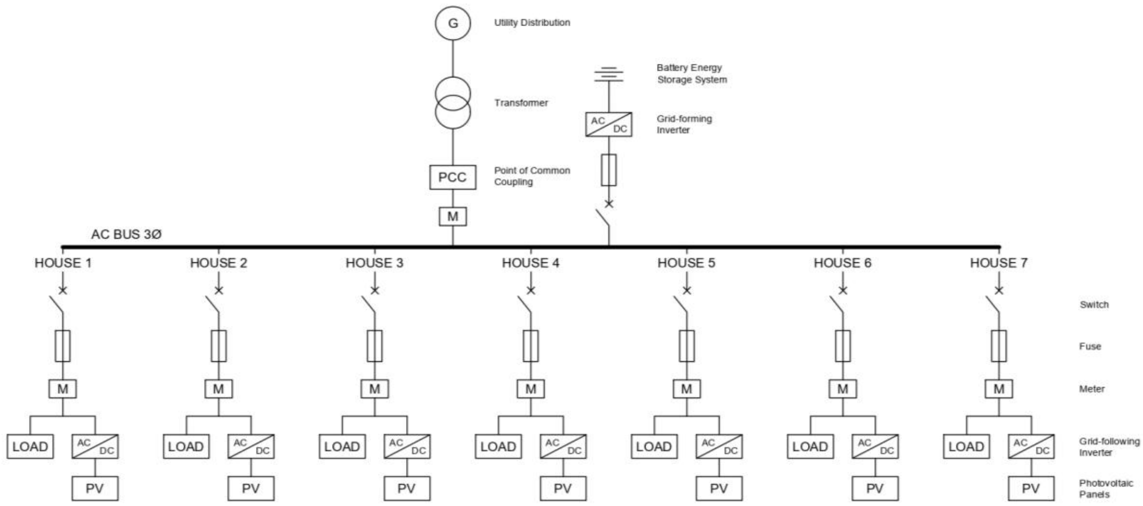

Figure 4. One Line Diagram for Energy Community

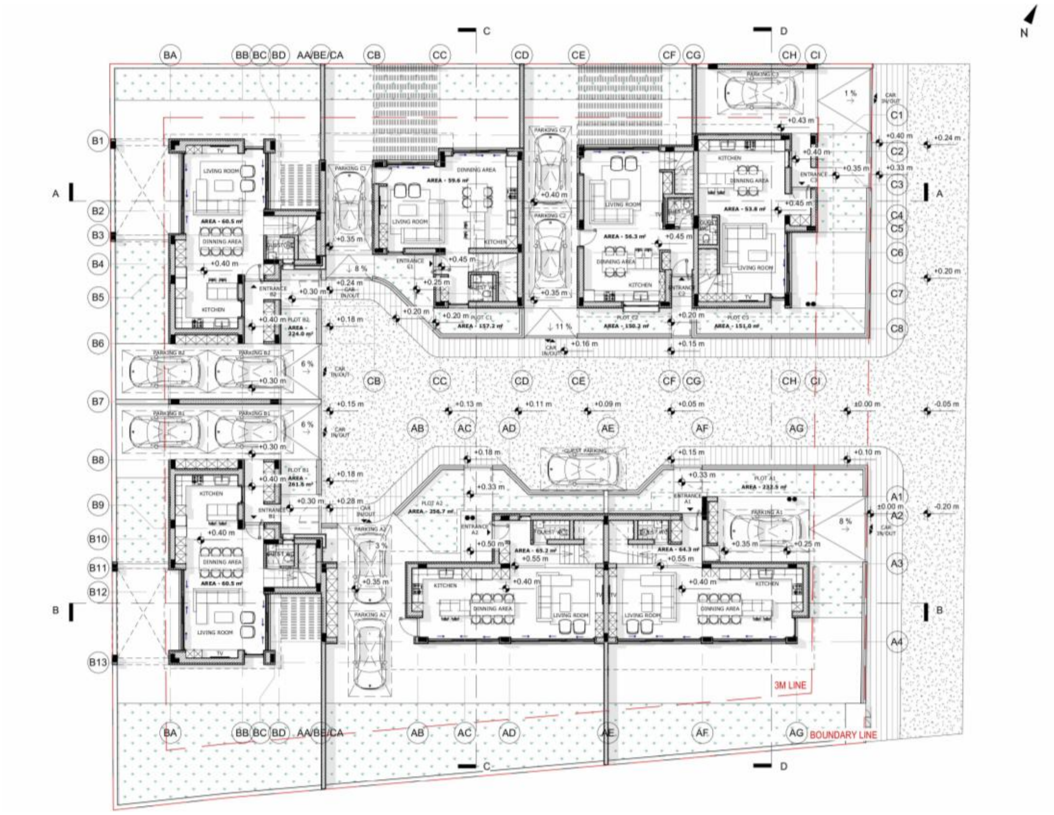

Figure 5. Ground Floor Plan of Energy Community

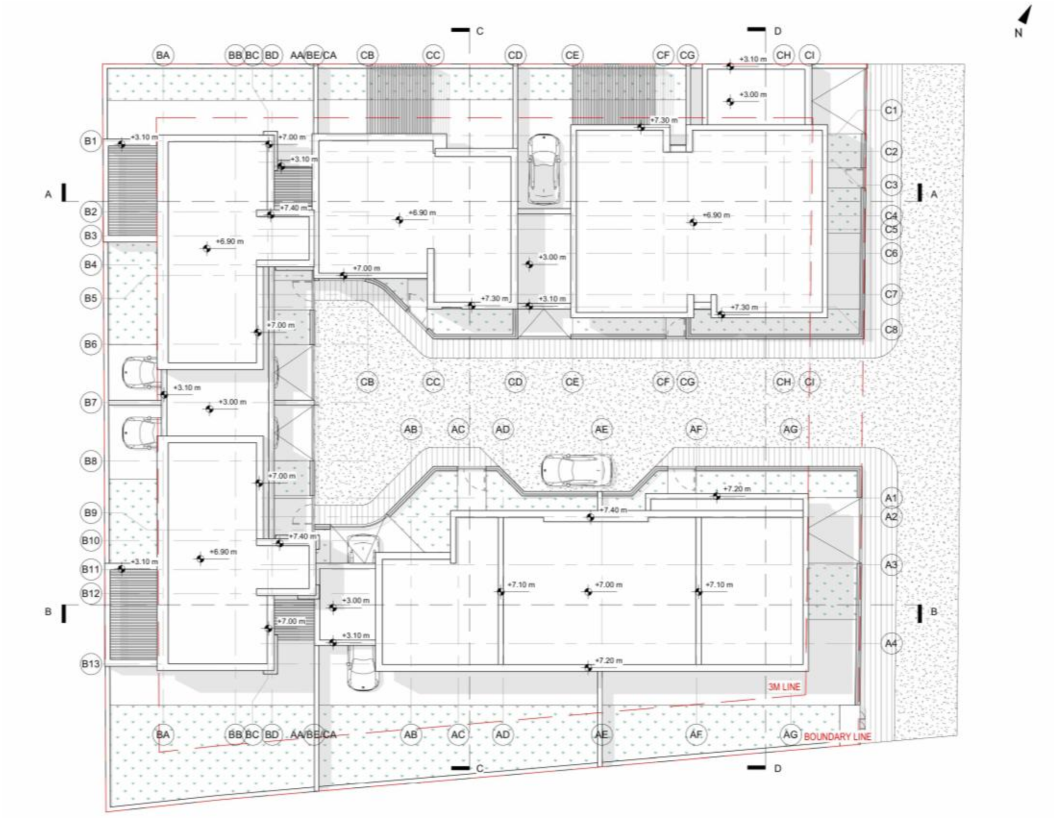

Figure 6. Roof Plan of Energy Community

3.3 System Sizing Logic

The determination of the optimal battery capacity relies on the energy balance method, governed by the following relationship:

$$E_{gen} = E_{inflex} + E_{flex}$$

where E_{gen} represents the energy generated by solar PV panels, E_{inflex} is the inflexible load, and E_{flex} is the flexible load, which includes EV charging and heat generation for thermal storage units.

To calculate the required battery capacity (E_{bat}), the generation profile must fully cover both the inflexible and flexible loads during active production intervals, leaving the remaining generation to be stored for consumption outside production hours:

$$E_{bat} = E_{gen} – (E_{inflex,prod} + E_{flex,prod})$$

To evaluate the economic viability of the system, a simplified payback framework is established. This model excludes operational maintenance costs and performance degradation, defining the economic equilibrium as follows:

$$C_{pv} + C_{bat} + C_{grid} = S_{annual} * L_{system}$$

where C_{pv} is the capital cost of solar panels, C_{bat} is the battery storage cost, C_{grid} is the grid infrastructure cost, S_{annual} represents the present value of annual financial savings from avoided electricity purchases, and L_{system} is the operational lifetime of the system.

This economic assessment assumes that the energy system is financed through either a one-time upfront payment or a structured installment plan. In the case of a one-time payment, future energy value is tied to current electricity prices, assuming that the asset value scales with inflation at the same rate as utility tariffs. Under the installment payment scenario, both the financing obligations and electricity prices are assumed to escalate concurrently at the inflation rate. As a result, inflation effects are neutralized within this framework and can be neglected.

The annual savings from avoided electricity purchases (S_{annual}) are calculated as the cumulative financial value of three distinct components:

- Covered flexible load: The flexible demand satisfied during active generation periods, valued at the minimum market electricity price.
- Covered inflexible load: The inflexible demand satisfied during active generation periods, valued at the market electricity price.

- Battery-covered inflexible load: The inflexible demand satisfied by stored battery energy outside generation periods, valued at the market electricity price.

Oversizing the generation capacity and battery storage to achieve total energy self-sufficiency is economically inefficient in many scenarios, as low-demand periods characterized by depressed electricity prices fail to generate sufficient returns to justify the additional capital expenditure.

Therefore, the economically optimal strategy for energy generation and battery sizing focuses on mitigating peak consumption intervals and utilizing stored energy during high-demand periods when electricity tariffs reach their peak values.

These relationships do not constitute the complete sizing algorithm but establish the conceptual logic later implemented within the Community Sizing System.

3.4 Digital Twin Lifecycle

The digital twin serves as a vital tool throughout the entire lifecycle of an energy community. Figure 7 illustrates the correlation between the development stages of the energy community and the corresponding evolutionary phases of its digital twin.

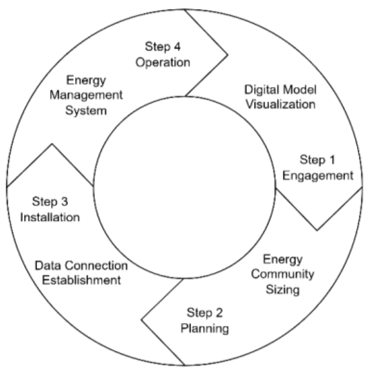

Figure 7. Energy Community Lifecycle Diagram

This technology plays a key role in engaging residents in energy community establishment. Because operational energy processes are not directly observable by most end-users, developing a digital model with an interactive web interface enhances user awareness and acts as an effective instrument for fostering community participation.

During the planning stage of the transition toward an autonomous or semi-autonomous energy community, it is necessary to determine the required capacity of PV systems and BESS. To identify the optimal configuration, the digital twin algorithm analyzes historical and forecasted data regarding energy generation, consumption profiles, electricity prices, initial and operational costs, and the desired payback period.

At the installation stage, the digital model is integrated with the control algorithm. Stable communication is established with sensors that transmit real-time data on energy generation and consumption, as well as battery and grid status.

During the operational phase, the digital twin is utilized to manage energy flows within the community. It enables autonomous decision-making to optimize energy distribution, storage scheduling, and electricity trading with the centralized grid. The accumulated data throughout the operational phase helps identify potential opportunities for system enhancement, thereby initiating a new iteration of the development lifecycle.

3.5 Digital Twin Infrastructure

To effectively support the energy community throughout the lifecycle stages, the digital twin must establish a continuous and seamless data exchange between its physical and digital components. Consequently, this architecture enables the physical world to be mirrored within the digital domain, while simultaneously allowing the digital environment to influence the physical one. Figure 8 represents the digital twin architecture.

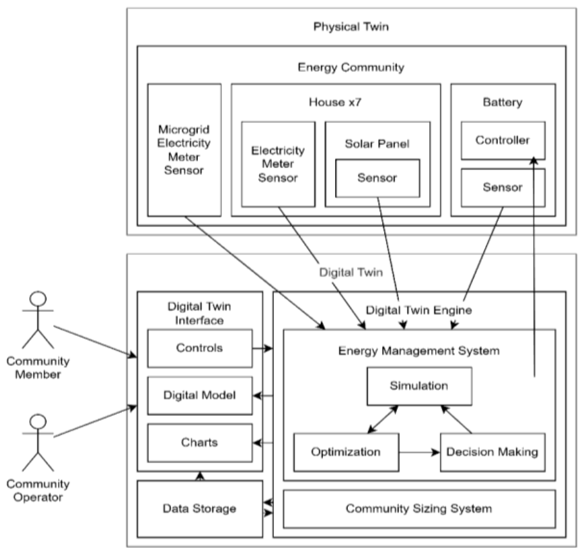

Figure 8. Digital Twin Architecture Diagram

During the energy community planning phase, the system operator utilizes a dedicated Community Sizing System accessible via an operator web interface to determine optimal capacity parameters.

Throughout the operational phase of the energy community, real-time data acquired from sensors embedded in household electricity meters, solar inverters, the shared battery system, and the microgrid primary meter is continuously transmitted to the Energy Management System. The software integrates live data into the predefined system interdependencies, analyzes the context, and simulates the future behavior of the system based on the specified optimization methods. The simulation results serve as the foundation for automated decision-making. A message containing the executed decision is transmitted to the battery inverter, which controls the entire energy flow within the community.

All calculated energy and financial flows, predictive forecasts, and executed optimization decisions are recorded in a database.

The transmission of live operational data alongside calculated energetic and financial flows to the digital model of the energy community transforms it into a digital shadow, which precisely reflects the actual state of the physical environment. Furthermore, the web interface provides community members with real-time access to flow charts, historical datasets, predictive forecasts, and the capacity to control optimization settings, thereby directly influencing the decision-making criteria of the EMS.

The capacity of the EMS to execute decisions that modify the state of the physical environment defines the transition from a digital shadow to a fully integrated digital twin of the community energy system. Because the proposed decision-making process is intended to operate autonomously without direct human intervention, relying on algorithmic execution, the framework is designed to satisfy Level 5 in the digital twin maturity classification framework.

3.6 Energy Control Hierarchy

To map these autonomous functions into the physical domain, the system establishes a structured control hierarchy. Within this architecture, the digital twin functions as a tertiary control level of the energy system, which manages economics and energy flow planning at a strategic level. Figure 9 presents a detailed description of the system at the contextual level.

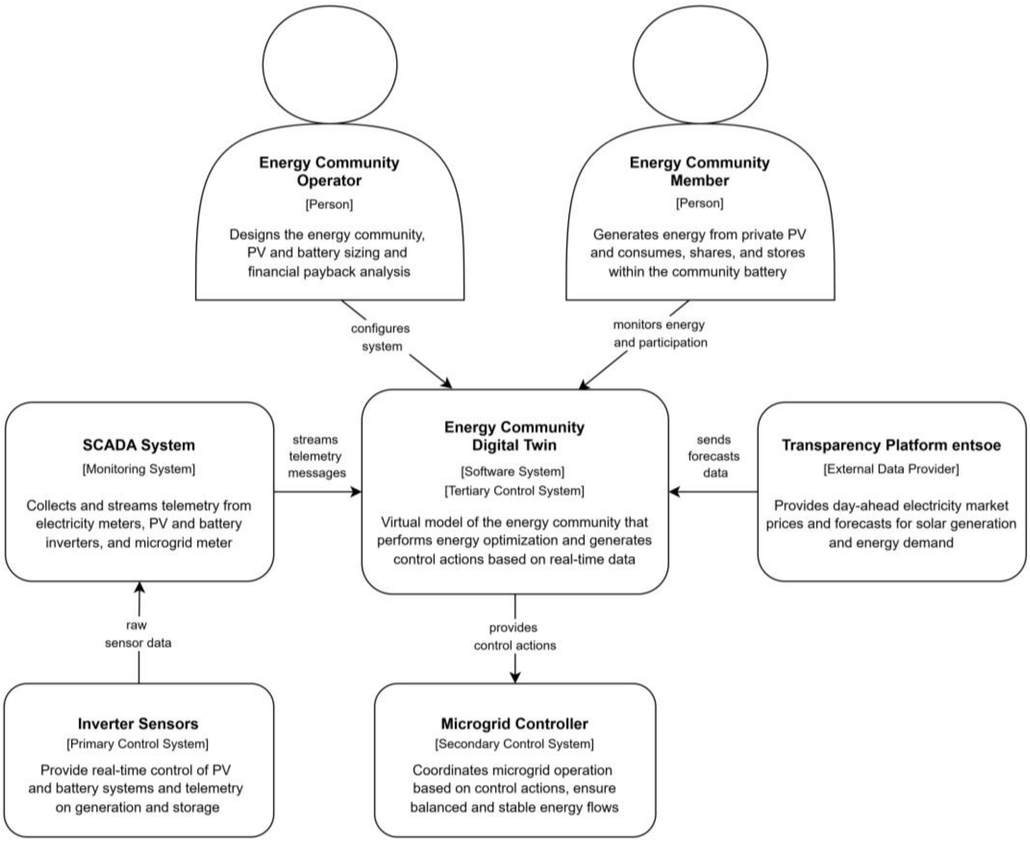

Figure 9. C4 Context Diagram for Digital Twin

The digital twin also acquires data regarding generation levels and battery status via a Supervisory Control and Data Acquisition (SCADA) system from the inverters. Operating at the micro-level, these inverters stabilize electricity parameters and correspond to the primary control level.

After computing the optimal energy flow, the digital twin transmits control actions to the microgrid controller, which acts as the secondary control level. This controller executes the received commands while maintaining stability and energy balance across the entire microgrid infrastructure.

The digital twin of the energy community features two distinct interfaces: the first is designed for community members to monitor energy flows and track their market participation, while the second is dedicated to the system operator for configuration purposes.

3.7 Software Container Architecture

While the control hierarchy defines the operational layers, the execution of these processes requires a robust software deployment. Figure 10 presents a detailed description of the system architecture at the container level.

The digital community model, encompassing both the buildings and the energy infrastructure, is developed utilizing Autodesk Revit. Autodesk Viewer is used to integrate the digital twin into the web interface designed for the energy community members.

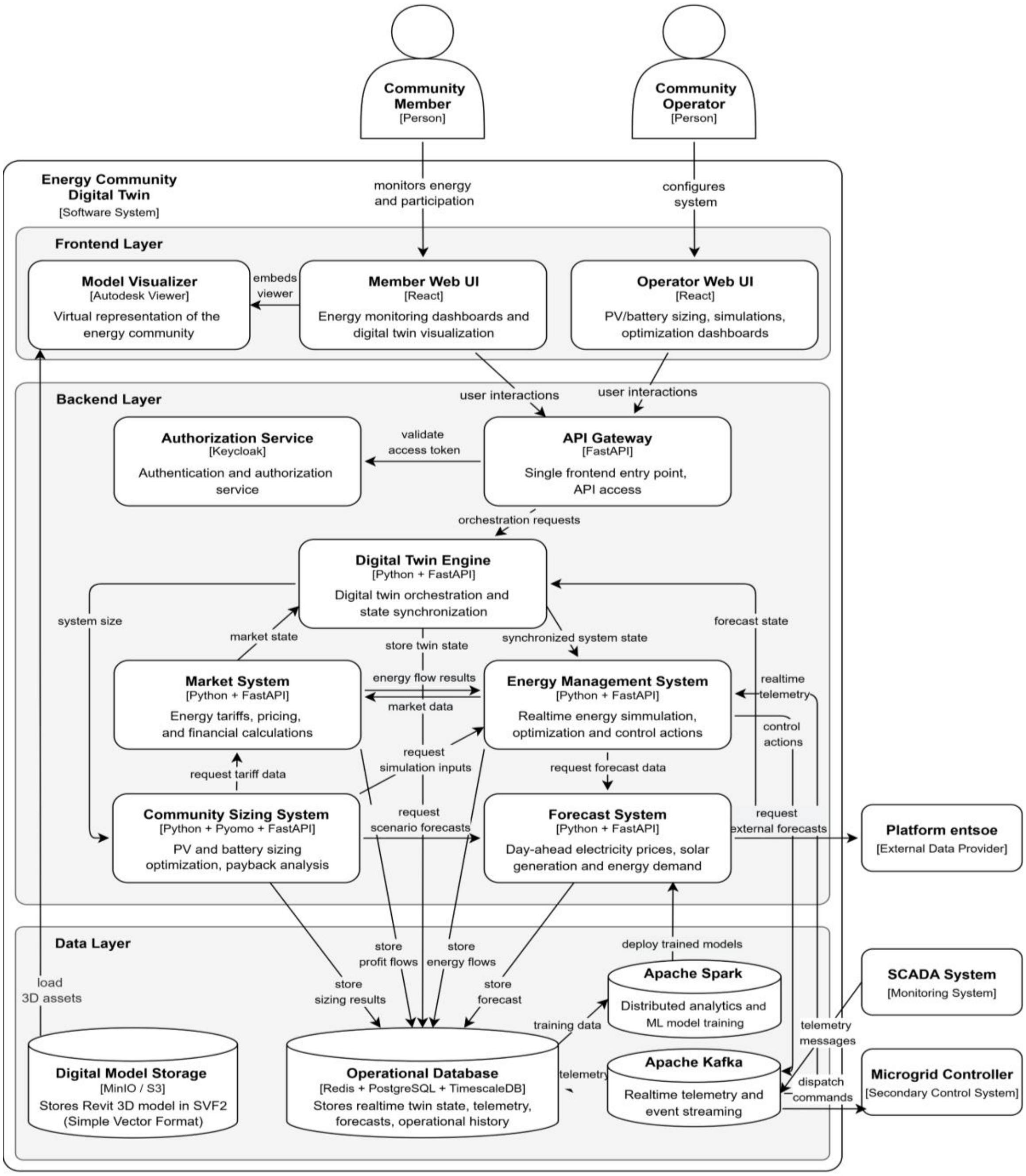

Figure 10. C4 Container Diagram for Digital Twin

The digital twin backend begins with an API Gateway, which serves as a unified entry point for the frontend infrastructure and verifies access tokens via the Authorization Service. The Digital Twin Engine is responsible for the orchestration and state synchronization of the digital twin.

The Community Sizing System utilizes tariff profiles from the Market System, alongside forecasted generation, consumption, and day-ahead electricity market prices from the Forecast System. Through simulations executed within the Energy Management System, it computes the optimal capacity ratio of PV panels and BESS with respect to the desired payback period.

The Energy Management System calculates optimal energy flows based on tariff data from the Market System and predictive forecasts from the Forecast System. Within the Market System, these optimized energy flows are translated into corresponding financial streams.

3.8 Functional Data Flows

This software architecture relies on the continuous flow of telemetry and external information throughout the system. Figure 11 presents a detailed description of the system data flows.

The digital twin relies on four primary information sources to govern its operations. The first source comprises the static parameters of the energy system established during the initial community sizing process.

The second source consists of BIM data in the SVF2 (Simple Vector Format) format, which contains geometric details of the buildings and the physical layout of the energy infrastructure. For the planning and design stages of this energy community, the framework utilizes a BIM model developed at the LOD 350.

The third source involves real-time sensor data collected via the PLC protocol. This data is verified and transmitted via a SCADA system into an Apache Kafka pipeline, which streams telemetry to the EMS. The executed energy flow distribution is then recorded in the central database. These operational energy flows are then translated into control actions and routed through Kafka to the microgrid controller, which dictates inverter setpoints to regulate battery activity.

The fourth source consists of external data retrieved from the ENTSO-E Transparency Platform, containing day-ahead electricity market prices, solar generation forecasts, and energy demand predictions. This external data is written to the database once every 24 hours and is later queried in 15-minute time slots to perform optimization computations.

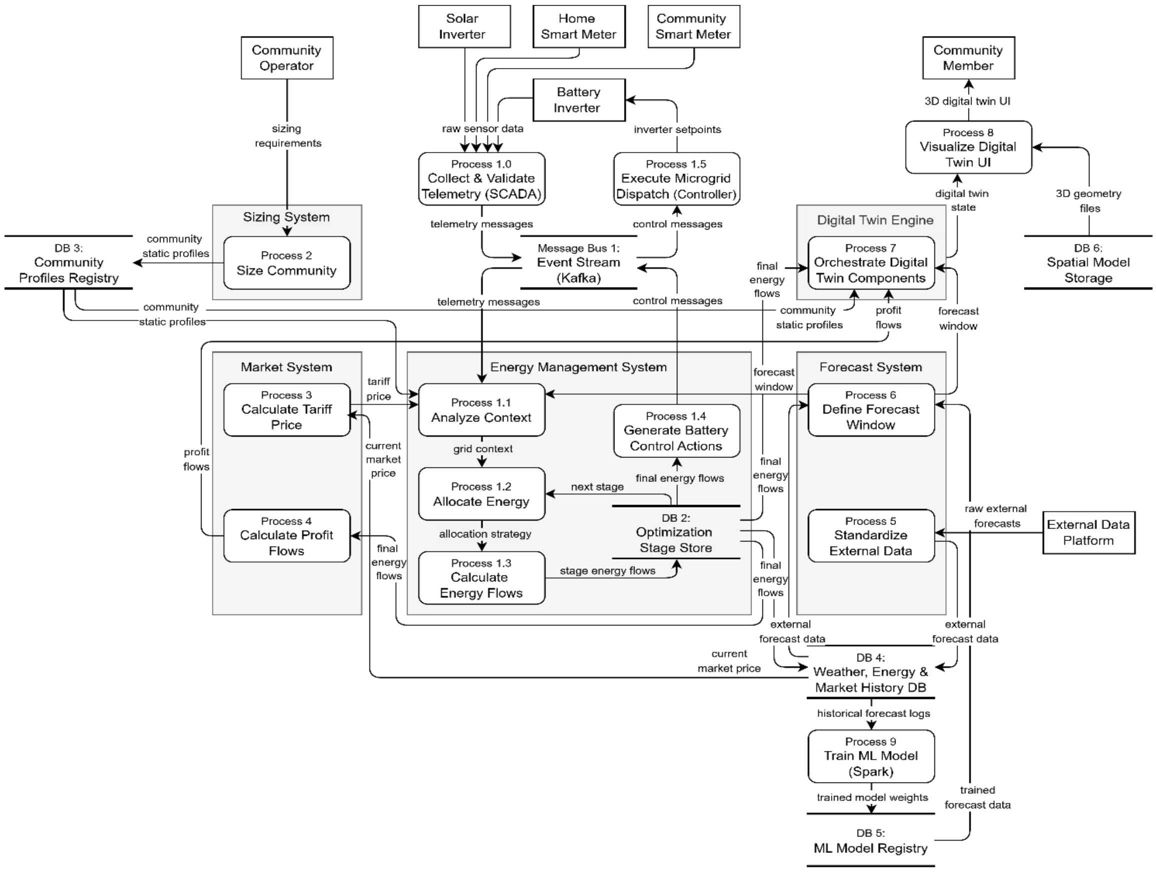

Figure 11. Data Flow Diagram for Digital Twin

Over time, the accumulated datasets enable the training of ML models utilizing Apache Spark. Once a trained model is deployed, predictive data supplied to the EMS can originate either from external resources or from the internal ML model.

Real-time data processing is required to enable a rapid response for real-time system management based on telemetry data. Conversely, batch processing can be utilized for ML training and historical data analysis.

For cloud computing and subsequent storage, the public cloud model of the Microsoft Azure ecosystem is selected in conjunction with the PaaS service model, which provides a ready-made environment for product development and operation. The Microsoft Azure ecosystem was selected due to its comprehensive set of tools for digital twin development and data processing.

4 Energy Management System Algorithms and Control Strategies

4.1 Energy Flow Principles

The primary objective of the EMS architecture is to dispatch the energy flows generated by the solar PV panels of individual houses to satisfy their respective electrical loads. Figure 12 illustrates the routing of these energy flows.

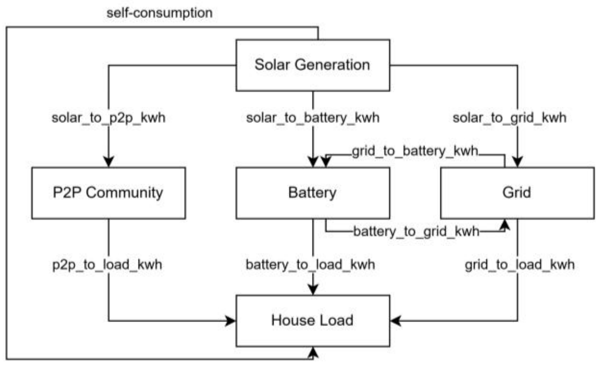

Figure 12. Energy Flow Diagram

In scenarios where a mismatch occurs between the generation and consumption profiles of an individual house, the discrepancies are balanced by the tradeable generation or consumption of other community houses, charge or discharge of the BESS, and energy import or export to the centralized power grid. The system also supports conditions where solar generation is insufficient to charge the battery or to execute predefined energy arbitrage strategies, and manages bidirectional energy flows directly between the centralized grid and the BESS.

4.2 Battery-Based Flow Control

These volumetric flows are regulated via the charging and discharging schedules of the BESS. Figure 13 presents the control mechanisms for the volume of exported and imported grid energy, alongside the source of community demand coverage.

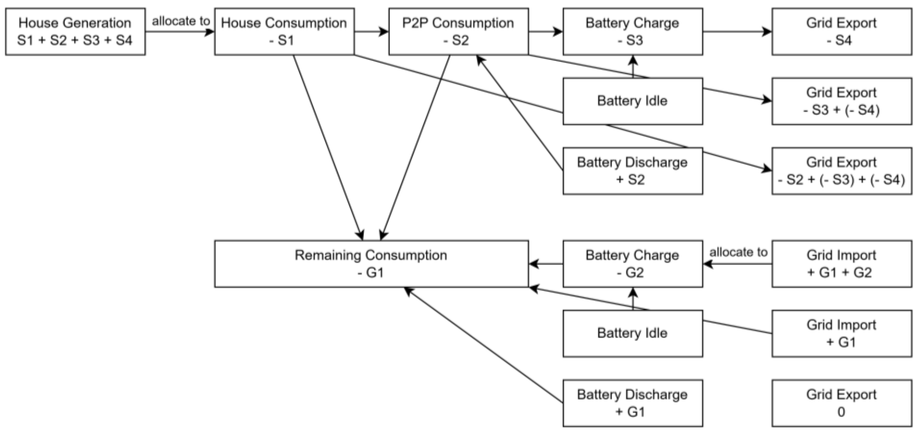

Figure 13. Energy Flow Control Mechanisms

The generated solar energy is distributed to the electrical loads according to a strict physical hierarchy. Initially, the energy is allocated to the producing house for local self-consumption. Any remaining surplus naturally flows into the microgrid infrastructure, where it is distributed to all community houses exhibiting an energy deficit and to the central BESS, provided it is in a charging state. If a surplus persists thereafter, the remaining excess energy is exported to the centralized power grid.

If the algorithm dictates that energy must be exported to the grid while community houses still exhibit a deficit, a battery discharging action is triggered to compensate for this internal demand. Consequently, this operation maintains a net surplus within the microgrid equal to the initial solar surplus, which is then exported to the centralized grid since the internal community demand has been fully offset.

Conversely, if a net deficit persists within the microgrid infrastructure, the required balancing energy is naturally imported from the centralized power grid.

An intentional increase in the volume of imported grid energy is achieved by initiating a battery charging process. This operational state can be executed during time intervals with zero solar generation or when the available solar power is insufficient to sustain the maximum charging rate of the BESS.

4.3 EMS Software Algorithm

The EMS within the digital twin is implemented via a Python-based algorithm. This algorithm regulates the execution sequences of the energy flow stages. Figure 14 illustrates the interdependencies between the primary elements of the EMS.

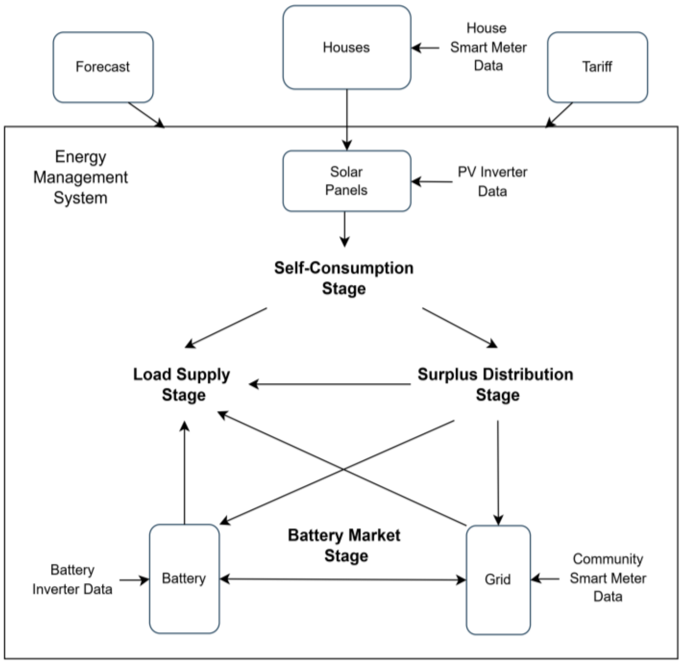

Figure 14. EMS Simplified Diagram

Initially, the allocation stage of the generated solar energy for local self-consumption is executed, which incorporates real-time telemetry regarding house demand and solar PV generation.

The next stage involves the identification and distribution of the energy surplus. This surplus can be fully mitigated either by the internal demand of other houses, energy charged to the BESS, or grid exports. The operational statuses of these components are continuously updated via real-time sensor data.

A similar logic applies to the load supply stage, which balances house deficits by utilizing the tradeable surplus generation from other houses, energy discharged from the BESS, or grid imports.

The final stage corresponds to the strategic utilization of the BESS, enabling the identification of additional requirements for battery charging from the grid and the selection of the optimal time intervals for this purpose. This stage identifies the financial viability of exporting electricity to the grid, managing the energy arbitrage process if it aligns with the overall energy community strategy. In such scenarios, the algorithm similarly determines the optimal time slots for battery discharging and grid exports.

Figure 15 illustrates the EMS architecture at the component level and demonstrates how these functional steps map into the software architecture. The visualization highlights data integration and exchange between containers.

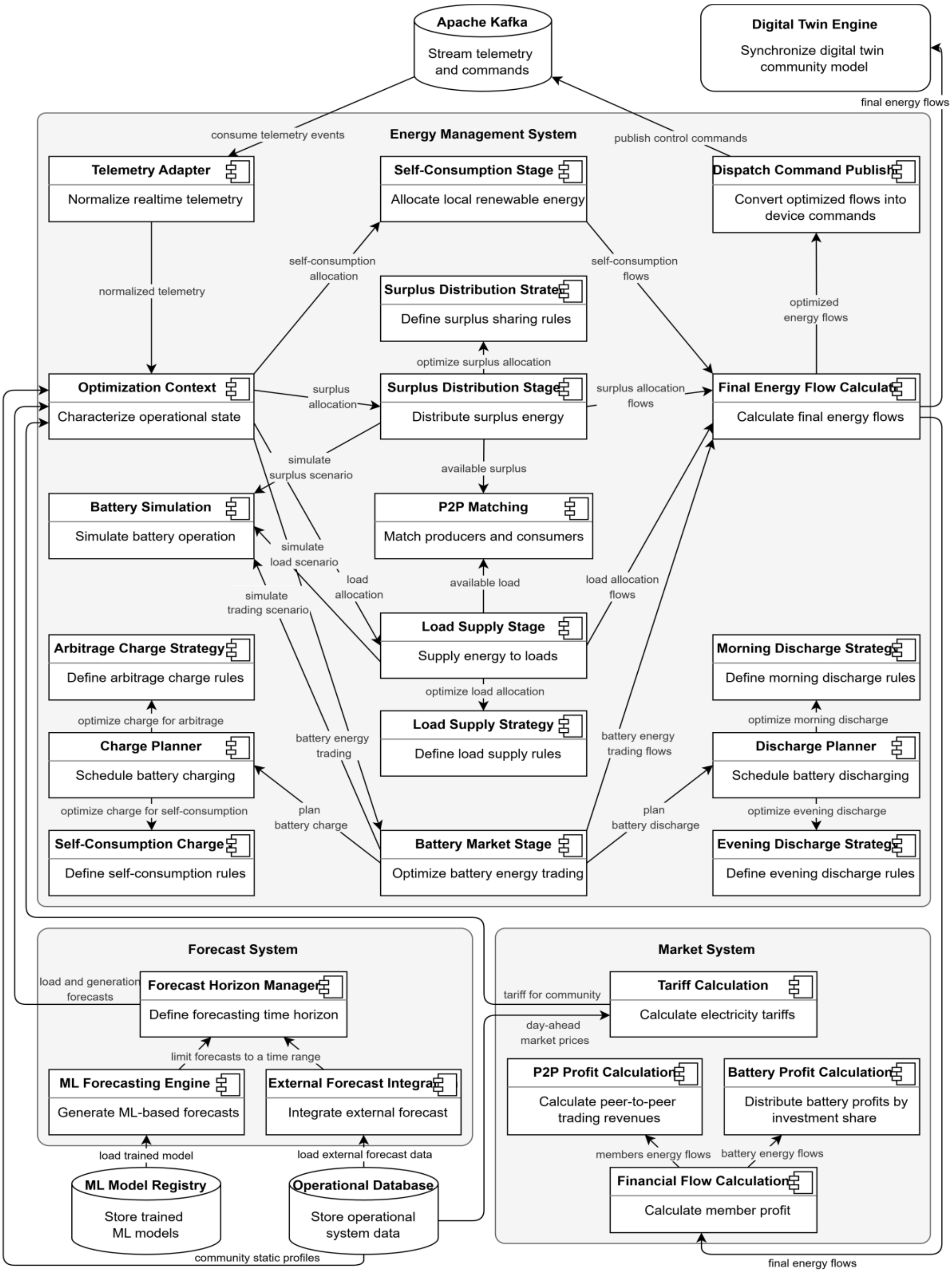

Figure 15. C4 Component Diagram for EMS

Determining the most economically viable utilization of the storage system incorporates day-ahead electricity market prices, solar generation forecasts, and energy demand predictions provided by the Forecast System. Financial benefits from buying or selling energy are calculated based on tariffs defining internal community and external grid relations. These tariff profiles are computed and supplied by the Market System.

To compute the optimal distribution of energy flows across the surplus distribution, load supply, and battery market stages, the system performs iterative battery state simulations based on forecasted generation, demand, and electricity prices. When a solar generation surplus is identified for internal trade, the energy allocated during the surplus stage is regulated by the P2P matching module. This module supplies the matched energy to the specific house exhibiting a deficit during the load supply stage.

Figure 16 outlines the procedural order for data integration and the sequential execution of the stages.

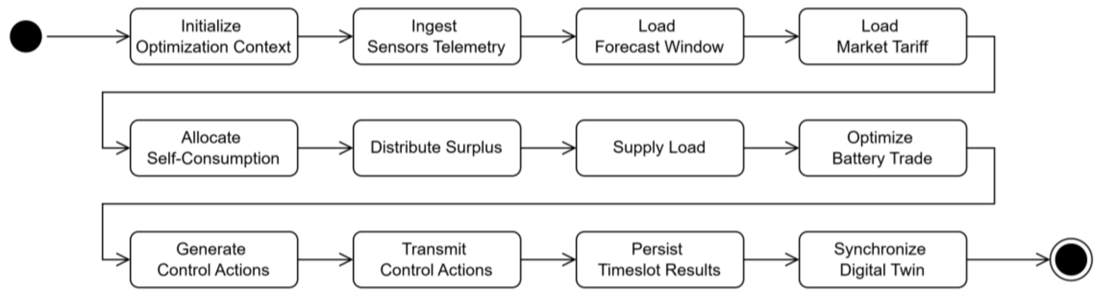

Figure 16. EMS Lifecycle Pipeline

Each energy distribution stage initiates with an evaluation of the updated contextual variables modified by the preceding stage and concludes by recording changes in intermediate energy distribution flows. Upon the execution of the final stage, the conclusive energy flows are established. This conclusive result is subsequently converted into control commands designated for execution by the central BESS.

4.4 House Operational States

Within the energy community framework, an individual house can transition between specific operational states. Figure 17 illustrates the operational states of an individual house and their execution sequence.

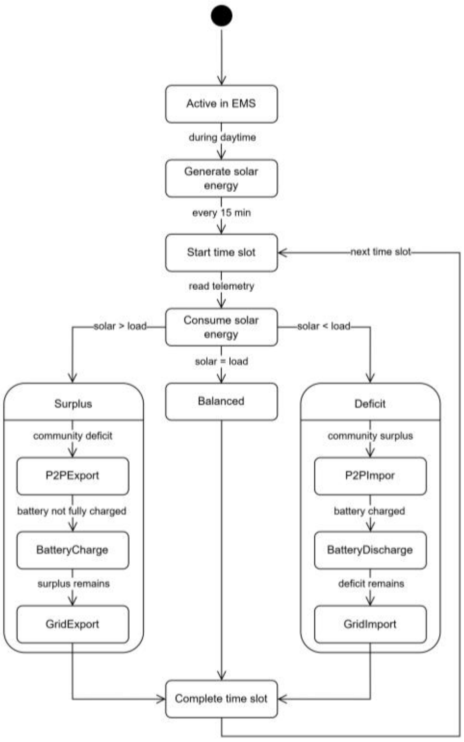

Figure 17. State Diagram for Energy Community House

Initially, the house generates solar energy, which is directly allocated for local self-consumption. If solar generation exceeds energy consumption, the house exhibits an energy surplus state. This surplus can be utilized to cover the energy deficits of other community houses, charge the central BESS, or be exported to the external grid, depending on the current contextual parameters.

Conversely, if energy consumption exceeds solar generation, the house exhibits an energy deficit state. This deficit can be mitigated by the tradeable surplus generation of other community houses, energy discharged from the BESS, or grid imports, depending on the contextual parameters.

If solar generation equals energy consumption, the house reaches a balanced state, which requires no active system intervention. The energy deficit and surplus analysis is executed continuously at each 15-minute time slot resolution.

4.5 Battery Operational States

The central BESS can similarly be categorized into distinct operational states. Figure 18 illustrates the operational states of the BESS and their execution sequence.

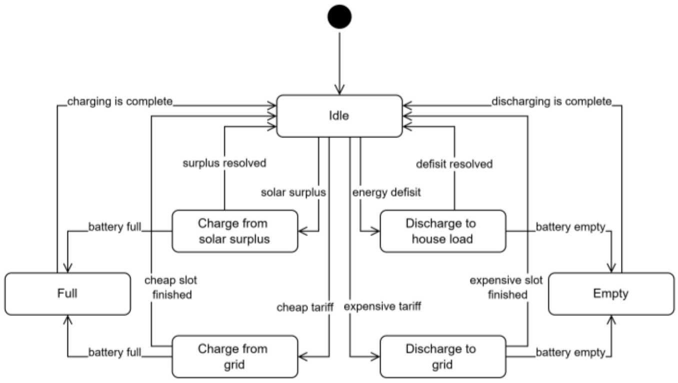

Figure 18. State Diagram for Battery Energy Storage System

The idle state is characterized by the absence of active charging or discharging, subject only to natural battery self-discharge.

From the idle state, the battery can initiate charging either from solar energy, provided a generation surplus exists, or from the grid, during time intervals corresponding to the optimal import prices determined by the simulation. The battery transitions back to the idle state once the generation surplus ceases, the selected grid charging time slot ends, or the maximum allowable State of Charge (SOC) level is reached.

Conversely, the battery can initiate discharging either to satisfy the energy demands of community houses during deficit periods, or to export energy to the grid during time intervals characterized by the optimal export prices determined by the simulation. The battery returns to the idle state after mitigating the house energy deficits, when the selected grid export time slot concludes, or when the battery is fully discharged to its minimum allowable SOC level.

4.6 Energy Dispatch Strategies

Figure 19 illustrates the operational logic and sequential conditions for energy distribution within the community. Figure 20 presents the dynamic interactions between the system components during the surplus distribution stage, while Figure 21 details the dynamic interactions during the load supply stage.

During the balancing of generation and consumption, each stage of the energy flow is executed sequentially for each individual house. The primary, unconditional action is the local self-consumption of the generated energy.

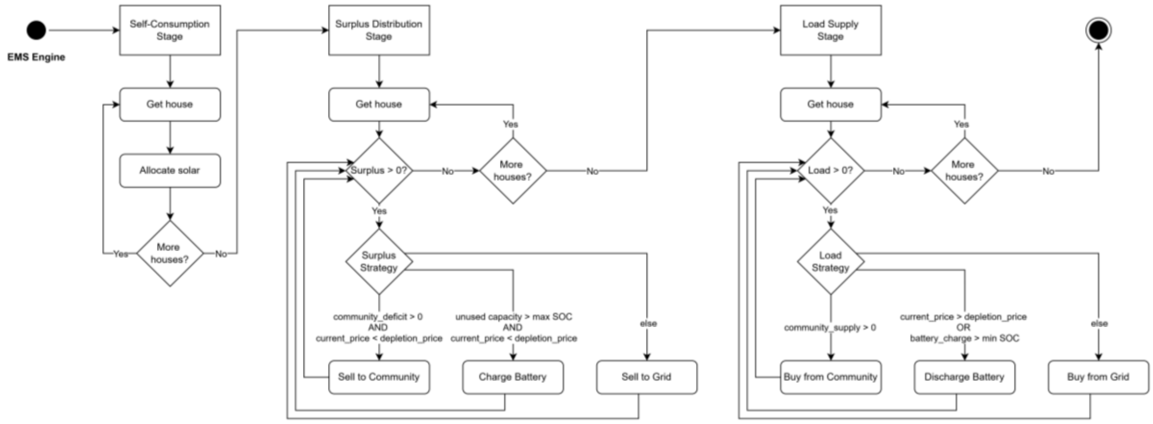

Figure 19. Activity Diagram for Energy Dispatch Stages

In scenarios where the available battery capacity is insufficient to fully cover the deficit, the expected grid price upon battery depletion is calculated as follows: grid electricity prices are sorted in descending order, and grid energy is allocated to cover the most expensive time intervals first. The maximum price among the time slots during which energy will be imported from the grid is defined as the expected grid price upon battery depletion.

If a house exhibits an energy surplus, the surplus dispatch strategy is applied. According to this strategy, if an energy deficit exists in other community houses and the current grid export price is lower than the expected grid price upon battery depletion, the surplus energy is traded internally with other community houses. If this internal trading is insufficient to mitigate the surplus fully, and the current SOC is lower than the maximum allowable SOC level, while the current grid export price remains lower than the expected grid price upon battery depletion, the remaining energy is stored in the central BESS. If a surplus persists thereafter, and in all other default cases, the excess energy is exported to the external power grid.

If a house exhibits an energy deficit, the load dispatch strategy is initiated. Under this strategy, if other community houses generate a tradeable energy surplus, the deficit house purchases this energy internally from the community. If internal generation is insufficient to cover the demand fully, and the battery SOC exceeds the minimum allowable SOC level, while the current grid import price is higher than the expected grid price upon battery depletion, the required energy is discharged from the BESS. If an energy deficit persists thereafter, and in all other default cases, the remaining energy demand is satisfied by grid imports.

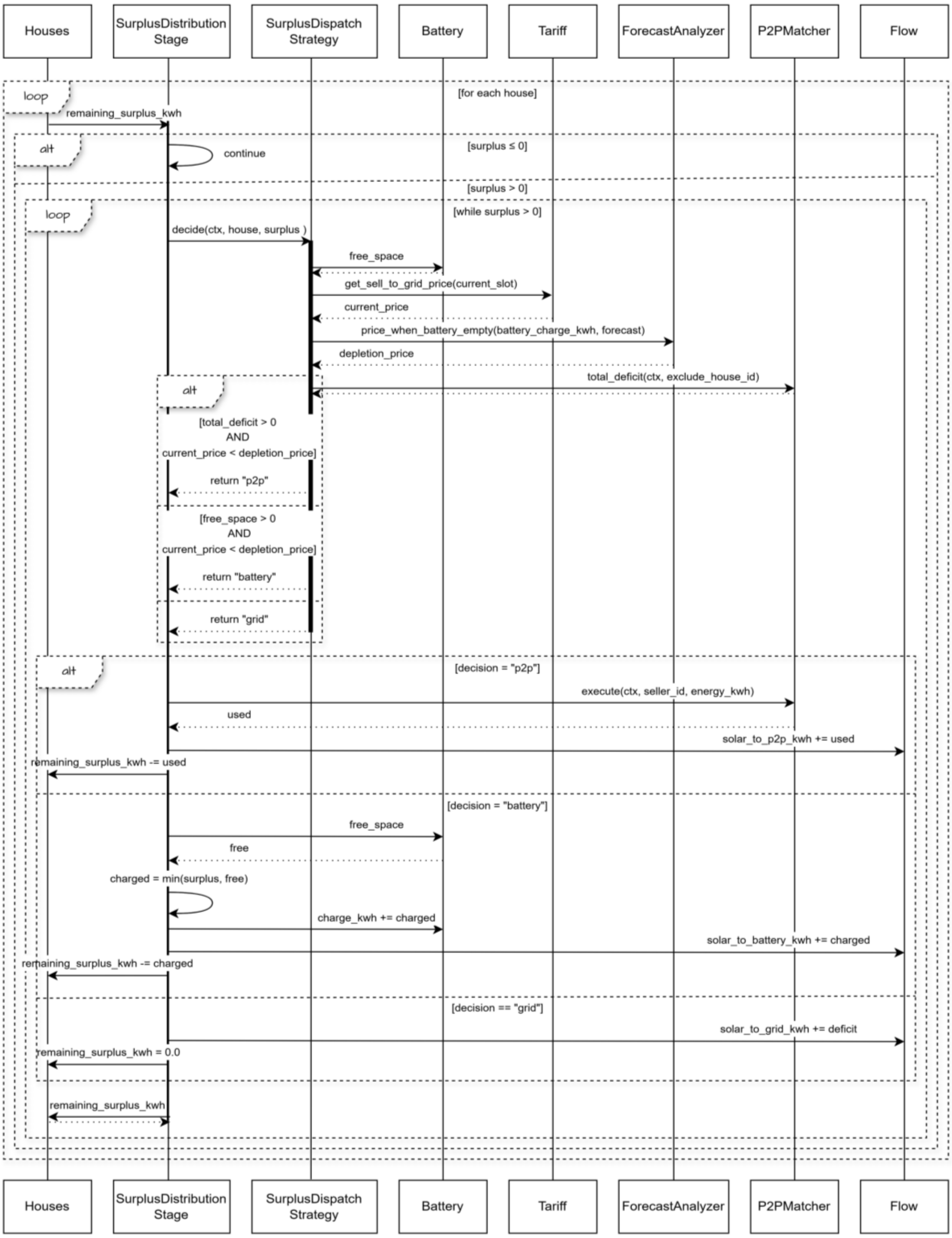

Figure 20. Sequence Diagram for Surplus Distribution

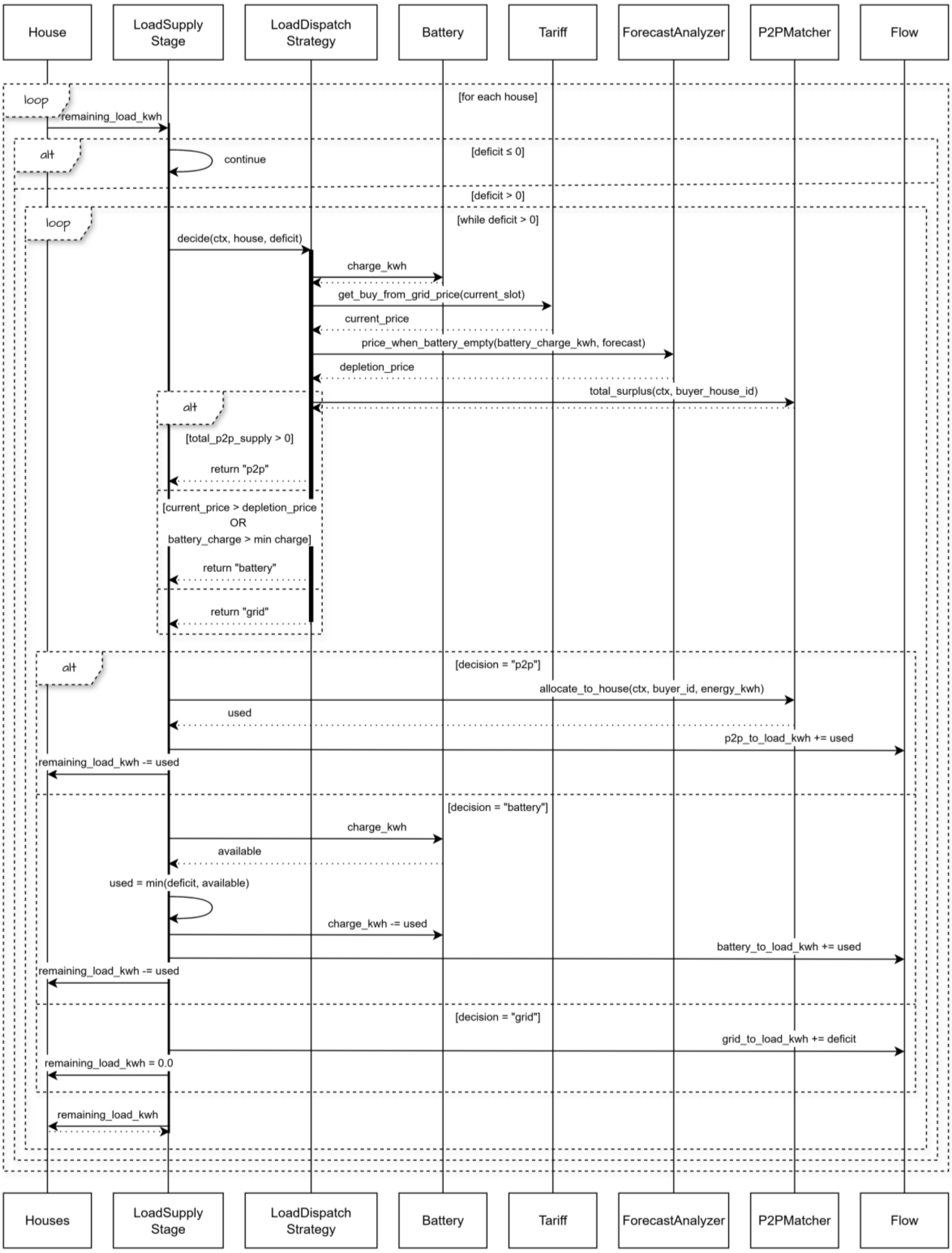

Figure 21. Sequence Diagram for Load Supply

4.7 Battery Market Strategy

After balancing the energy surplus and load supply, the battery market stage is initiated to plan the charging and discharging schedules of the BESS. Figure 22 illustrates the operational logic and sequential conditions for storage management. Figure 23 presents the dynamic interactions between system components during the battery charging planning stage, while Figure 24 (details the dynamic interactions during the battery discharging planning stage.

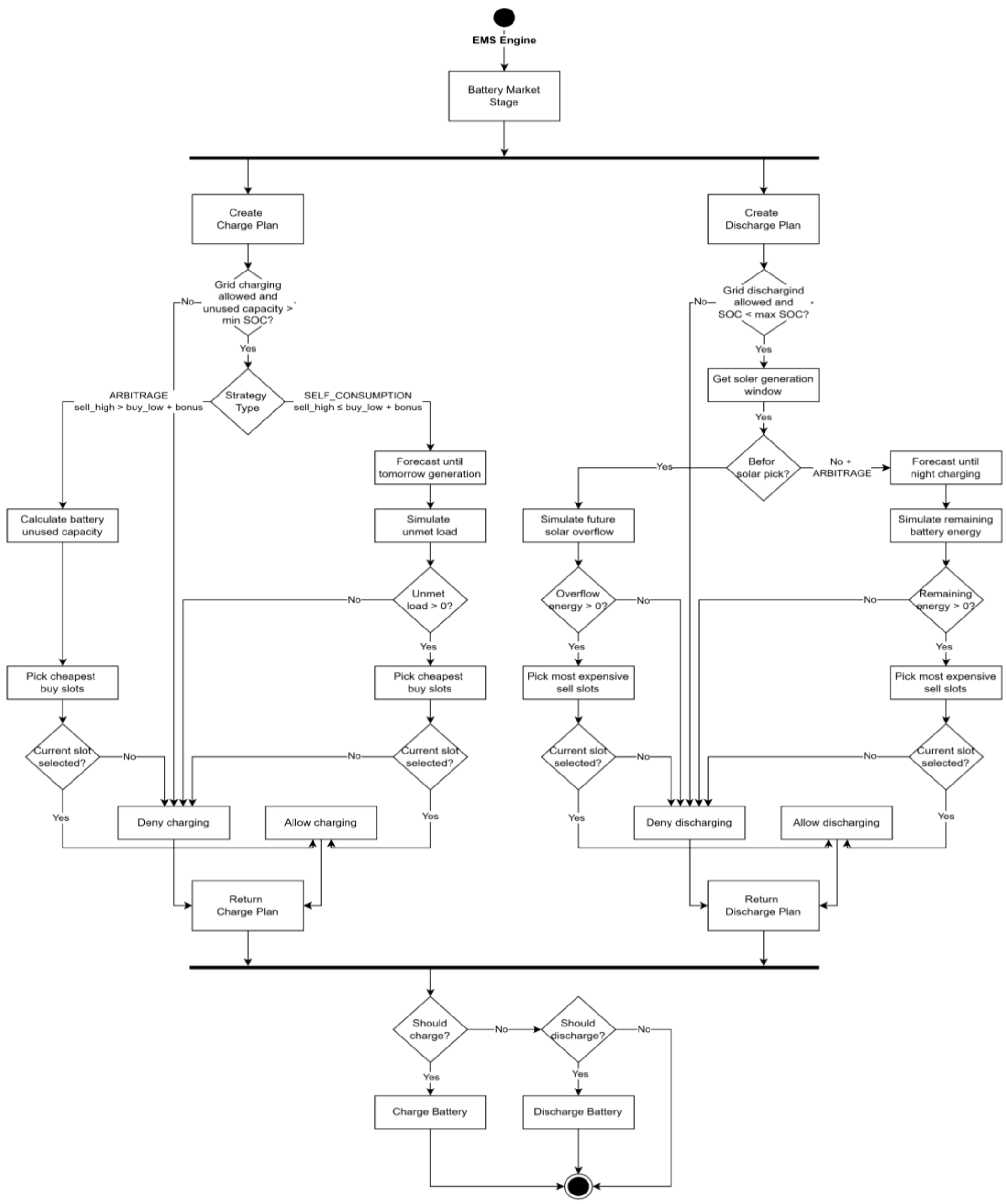

Figure 22. Activity Diagram for Battery Market Stage

If charging is permitted and the current SOC is lower than the maximum allowable SOC level, a battery charging plan is formulated. Within the day-ahead horizon, if the maximum grid export price exceeds the minimum grid import price combined with a self-consumption remuneration (if applicable), then charging is executed according to the energy arbitrage strategy. Under this strategy, the remaining available capacity of the BESS is charged up to the maximum allowable SOC level during the time intervals characterized by the lowest electricity purchase prices.

Otherwise, the self-consumption strategy is selected, aimed at determining the exact volume of energy required by the community to cover the solar generation deficit and achieve full community autonomy. Under this strategy, generation and consumption are simulated until the forecasted peak solar generation period of the following day. It represents the point at which the probability of satisfying demand through internal generation is expected to be highest. In scenarios where an unsatisfied load exists, it is aggregated and stored in the battery during the time intervals characterized by the lowest purchase prices.

If grid export is permitted and the battery SOC is higher than the minimum allowable charge level, a battery discharging plan is formulated. Before the peak of solar generation, the battery is discharged to clear storage capacity for accumulating the forecasted surplus of solar generation remaining after self-consumption and internal trading with other community members for the current day. This surplus is allocated for export during the time slots characterized by the maximum electricity prices.

Exporting energy after the peak of solar generation occurs, provided that the energy arbitrage strategy is active within the current context. In this case, time slots for battery charging during low grid import price periods are identified, and the remaining charge level in the battery at the moment of the earliest charging slot is simulated. This volume of energy is then sold during the time slots with the maximum electricity prices.

At each time slot, the battery charging and discharging schedules are adjusted as a result of the sequential execution of the algorithm. This adjustment is necessary to correct discrepancies between forecasted and actual generation and consumption profiles. Within each time interval, the availability of free capacity for charging or allowable charge for discharging is re-evaluated.

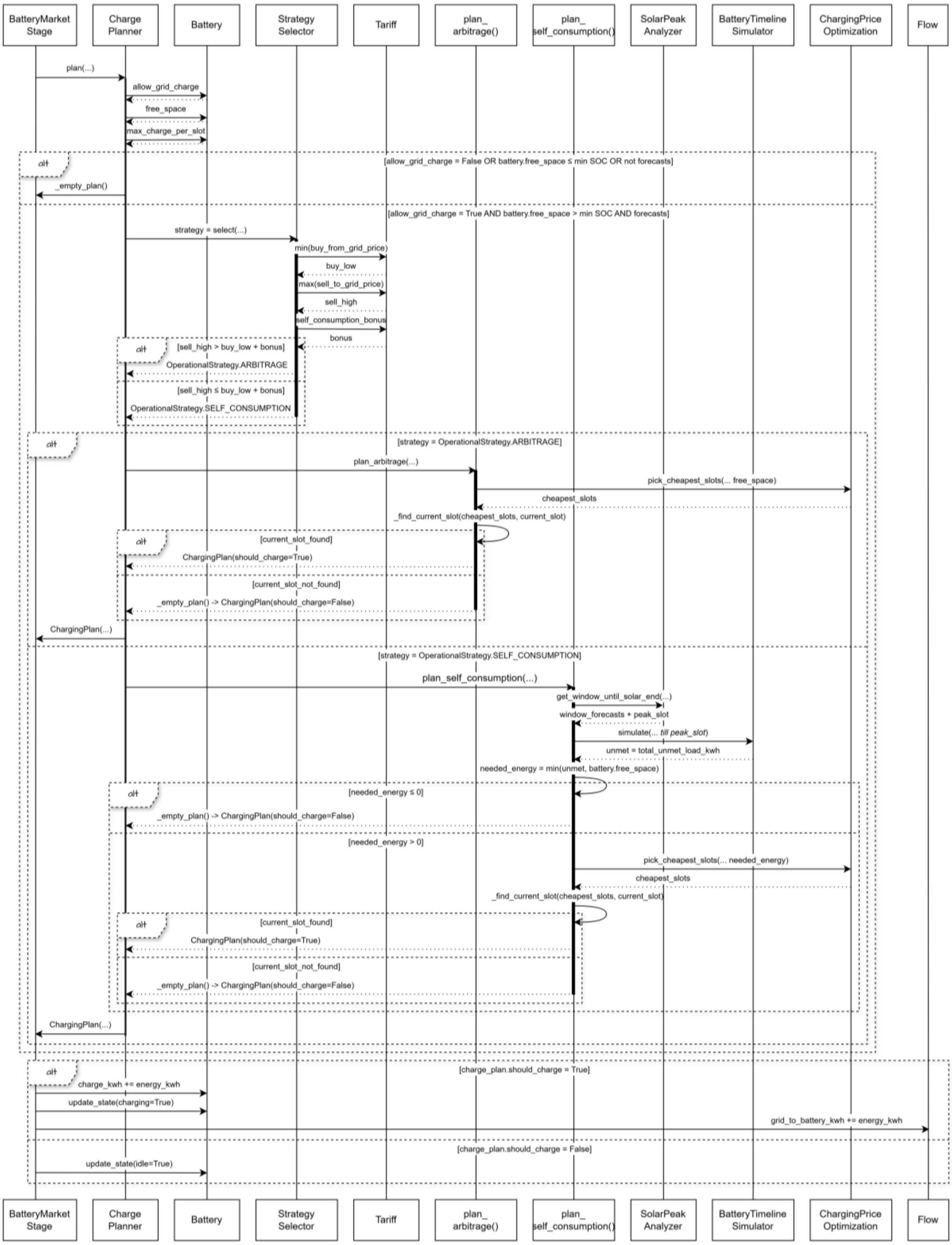

Figure 23. Sequence Diagram for Charge Planner

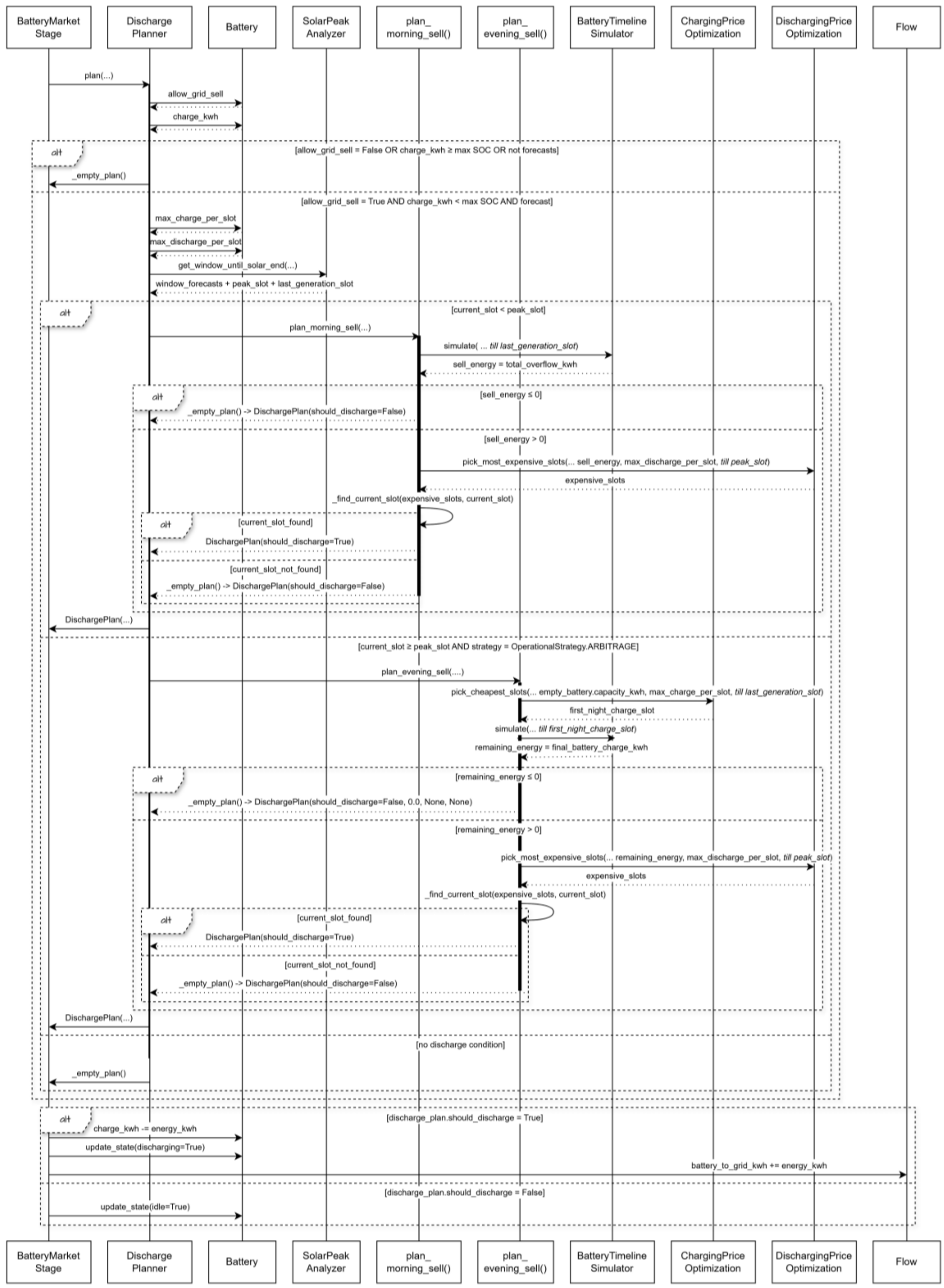

Figure 24. Sequence Diagram for Discharge Planner

5 Conclusion and Perspectives

5.1 EMS Simulation Results

Within this research, a dedicated digital twin architecture has been developed, in which the proposed EMS software algorithm serves as the pivotal component facilitating autonomous decision-making. To validate its operational efficiency, an energy flow simulation was executed, followed by an evaluation of the financial distribution. Grid and market data for the Greek power system were sourced from the ENTSO-E Transparency Platform for the specific operational date of July 15, 2025. While the calculated capacities of the PV panels and the BESS do not necessarily represent optimized sizing, they conform to the proportions of house sizes and consumption profiles.

The community consists of seven houses with asymmetric parameters: House 1 and House 2 possess 7 kW PV and a 20% investment share for the 150 kWh central BESS; House 3 and House 4 possess 5 kW PV and a 15% BESS share; House 5 has 5 kW PV and a 10% BESS share; House 6 and House 7 possess 4 kW PV and a 10% BESS share.

The baseline consumption pattern, derived from the Greek national average, is scaled down proportionally to individual house sizes. This reference profile is replicated across House 1, House 3, and House 6 at relative ratios of 1.25, 1.00, and 0.75, respectively. House 2, House 4, and House 5 apply identical scaling, but their daytime consumption during standard working hours is reduced to the base load level. House 7 exhibits intensified nocturnal appliance utilization relative to the other groups.

The simulation framework assumes zero self-consumption remuneration, a 10–90% SOC operating range to mitigate battery degradation, and a mandatory 50% SOC boundary at both the beginning and end of the 24-hour cycle. Grid energy exports are remunerated at the market purchase price. Under the selected economic model, houses purchase energy during energy deficits from other members, the battery, or the grid at market rates. Direct P2P sales revenue is retained fully by the selling house. Financial flows involving the BESS, including revenue from battery discharges or costs from battery charging, are allocated among community members strictly proportional to their investment shares.

Figure 25 - Figure 35 illustrate the hourly energy and financial distribution between the houses, the BESS, and the grid. The simulation results indicate that the 150 kWh BESS capacity is insufficient to store the total solar surplus. Consequently, the EMS scheduled grid exports during peak-price solar intervals before and after the main charging cycle, specifically at 07:00, 08:00, 15:00, 16:00, and 17:00.

Because initial community demand was insufficient to lower the SOC from 50% to 10% before peak solar generation, a 12.04 kWh surplus was exported to the grid at the highest morning market price at 06:00 to release storage capacity. Similarly, evening demand could not naturally reduce the SOC from 90% to the mandatory 50% boundary by midnight, necessitating a 7.47 kWh grid export at the peak evening price slot at 20:00.

The operational logic is highly representative at 17:00, where solar generation first satisfies local house demand, and remaining surpluses are dynamically routed to houses facing a deficit. Since the BESS reaches maximum SOC by this interval, securing a higher export value than during the earlier charging phase, the remaining unallocated surplus is automatically exported to the grid.

The following financial metrics quantify the economic viability of the established energy community equipped with PV panels and a BESS. Over the 24-hour cycle, the community consumed 194.72 kWh and generated 231.41 kWh. In the absence of an LES infrastructure, the daily electricity cost would amount to 18.56 EUR. Utilizing PV panels with grid export capabilities but without a BESS reduces the cost of covering the energy deficit to 5.29 EUR. Conversely, the full integration of an LEC featuring both PV panels and a BESS transitions the community to a net revenue of 4.18 EUR for the analyzed operational date.

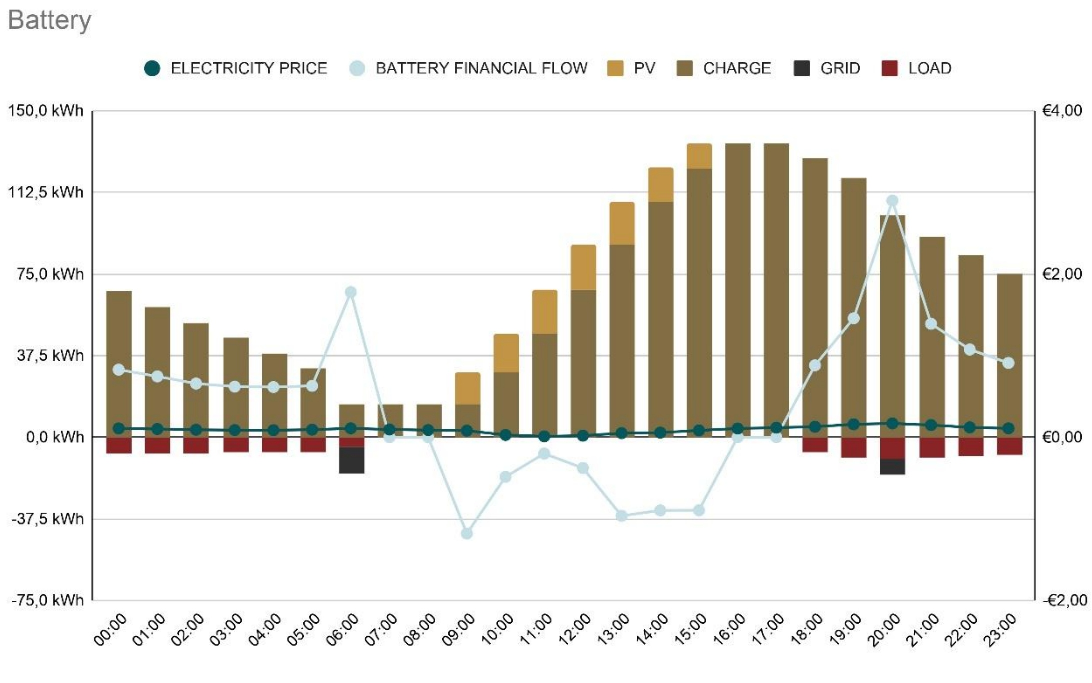

Figure 25. Distribution of Battery Energy and Financial Flows

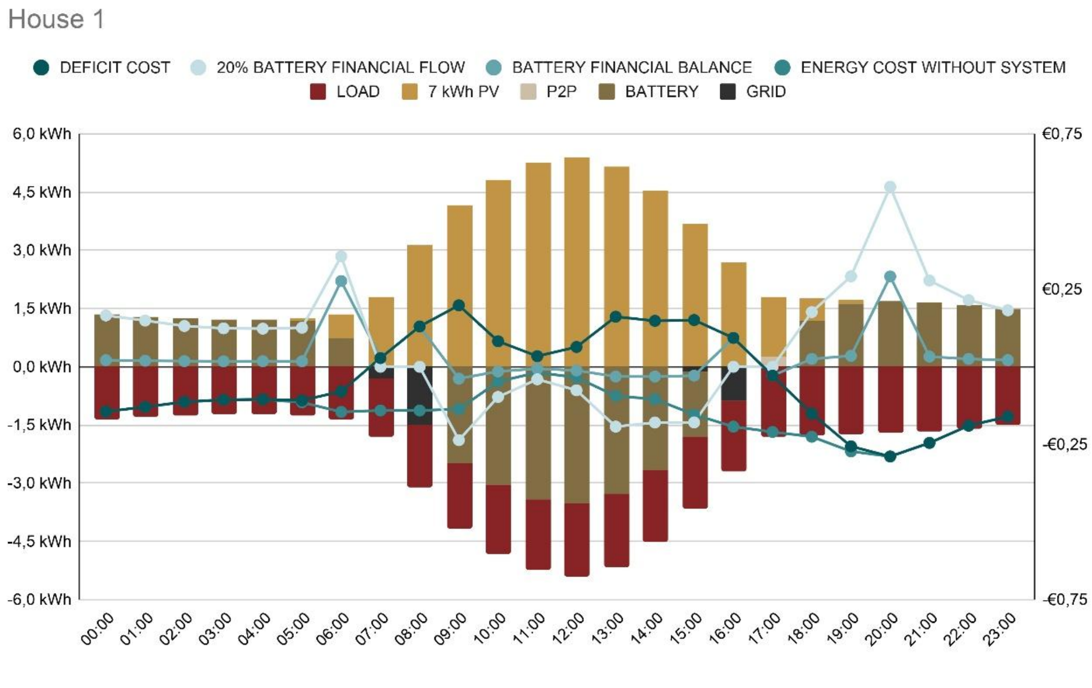

Figure 26. Energy and Financial Flows Distribution for House 1

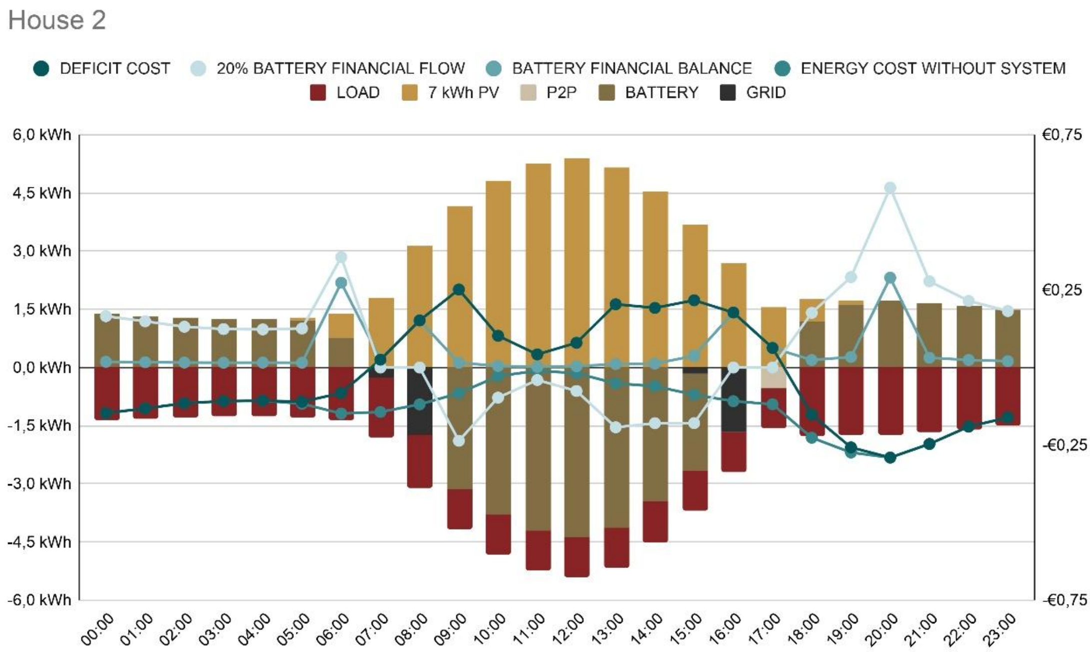

Figure 27. Energy and Financial Flows Distribution for House 2

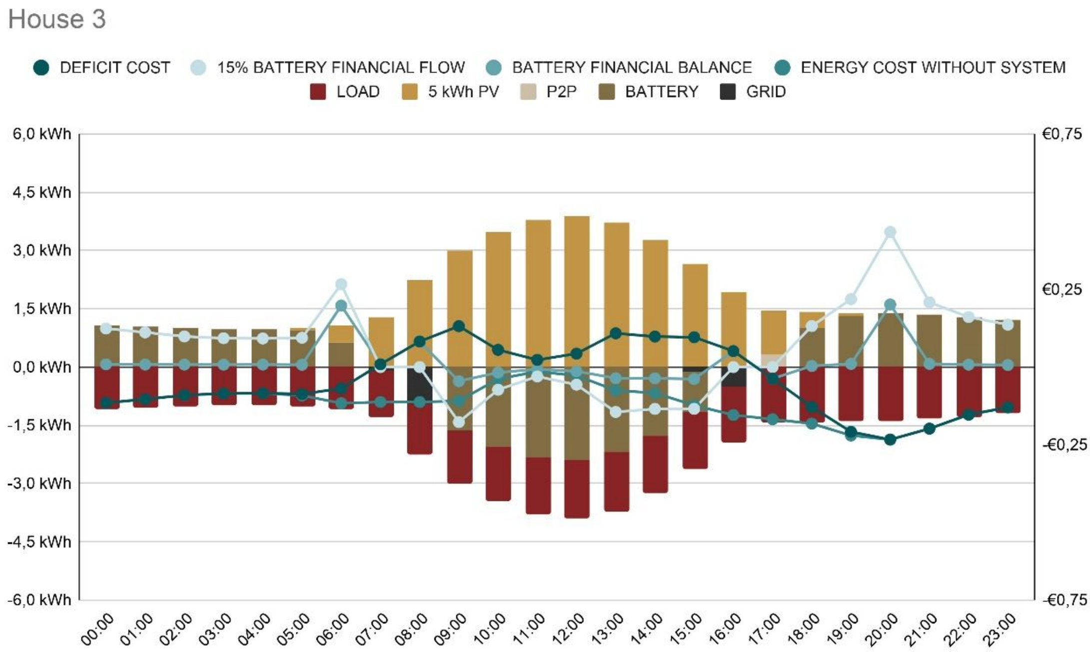

Figure 28. Energy and Financial Flows Distribution for House 3

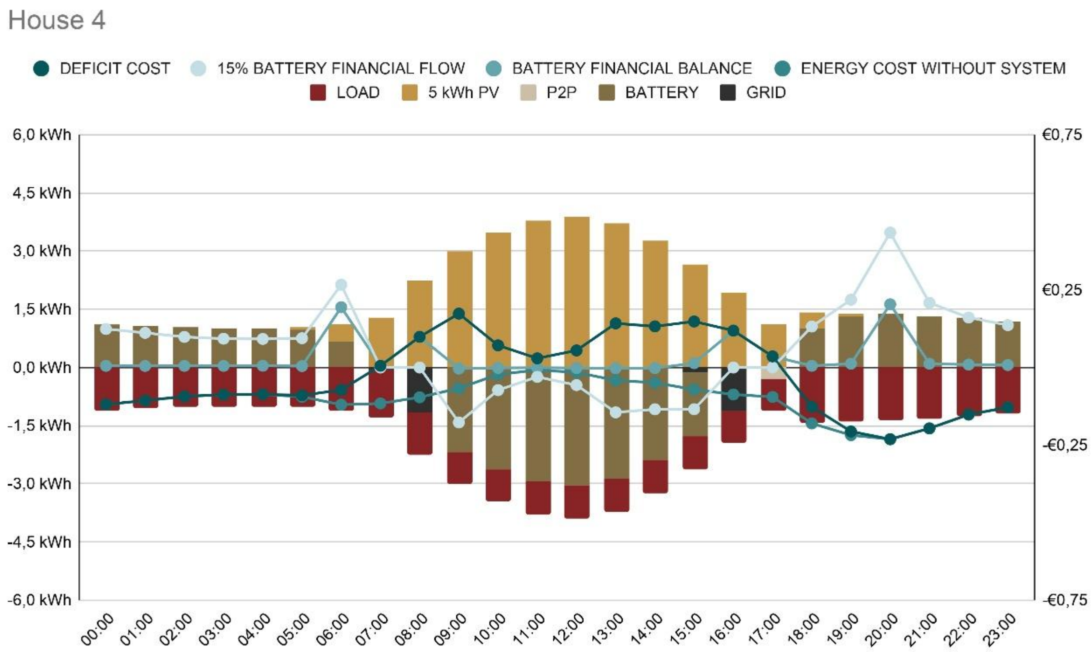

Figure 29. Energy and Financial Flows Distribution for House 4

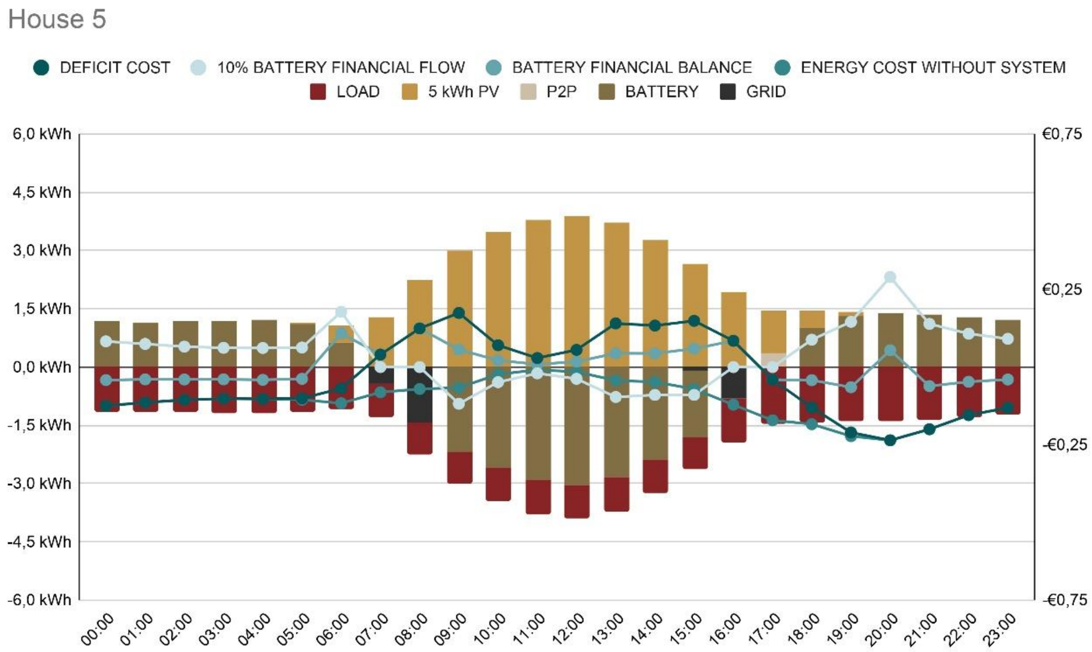

Figure 30. Energy and Financial Flows Distribution for House 5

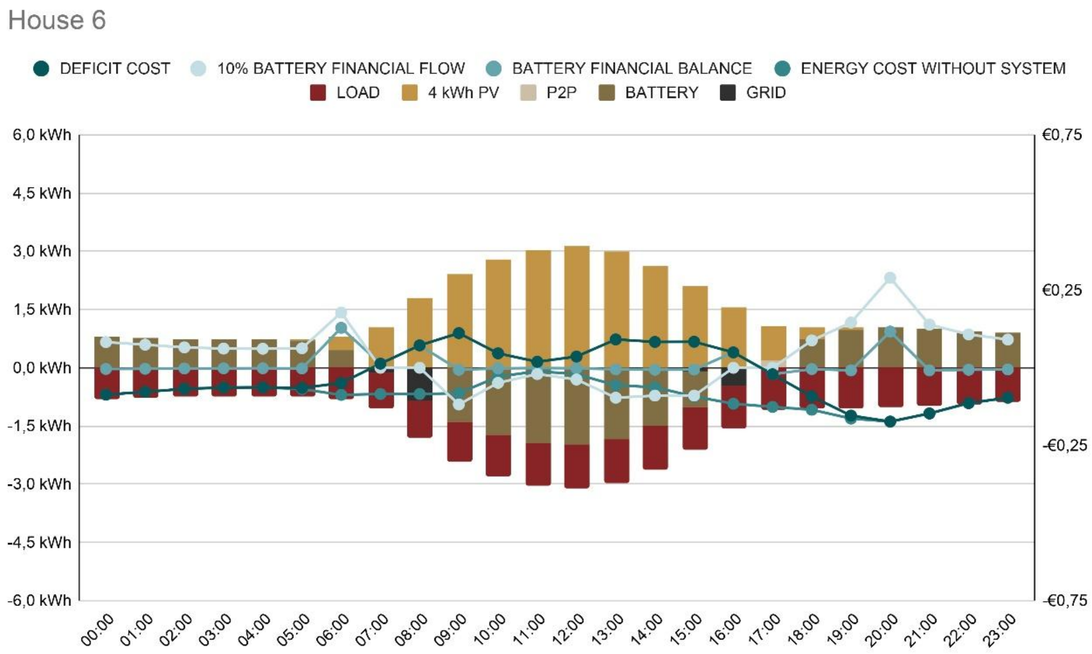

Figure 31. Energy and Financial Flows Distribution for House 6

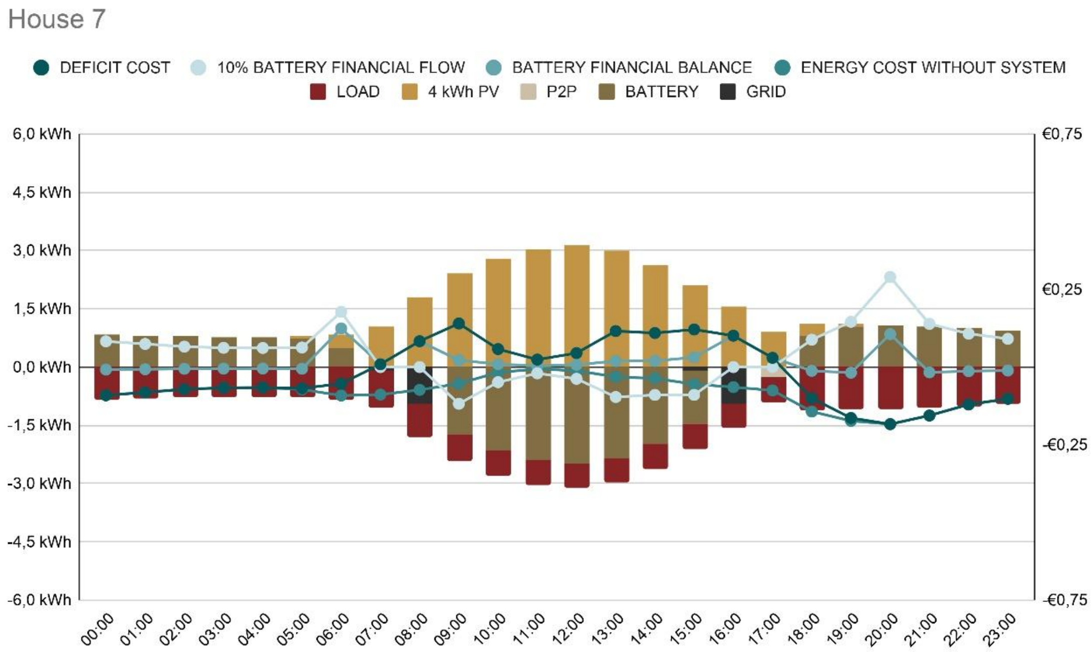

Figure 32. Energy and Financial Flows Distribution for House 7

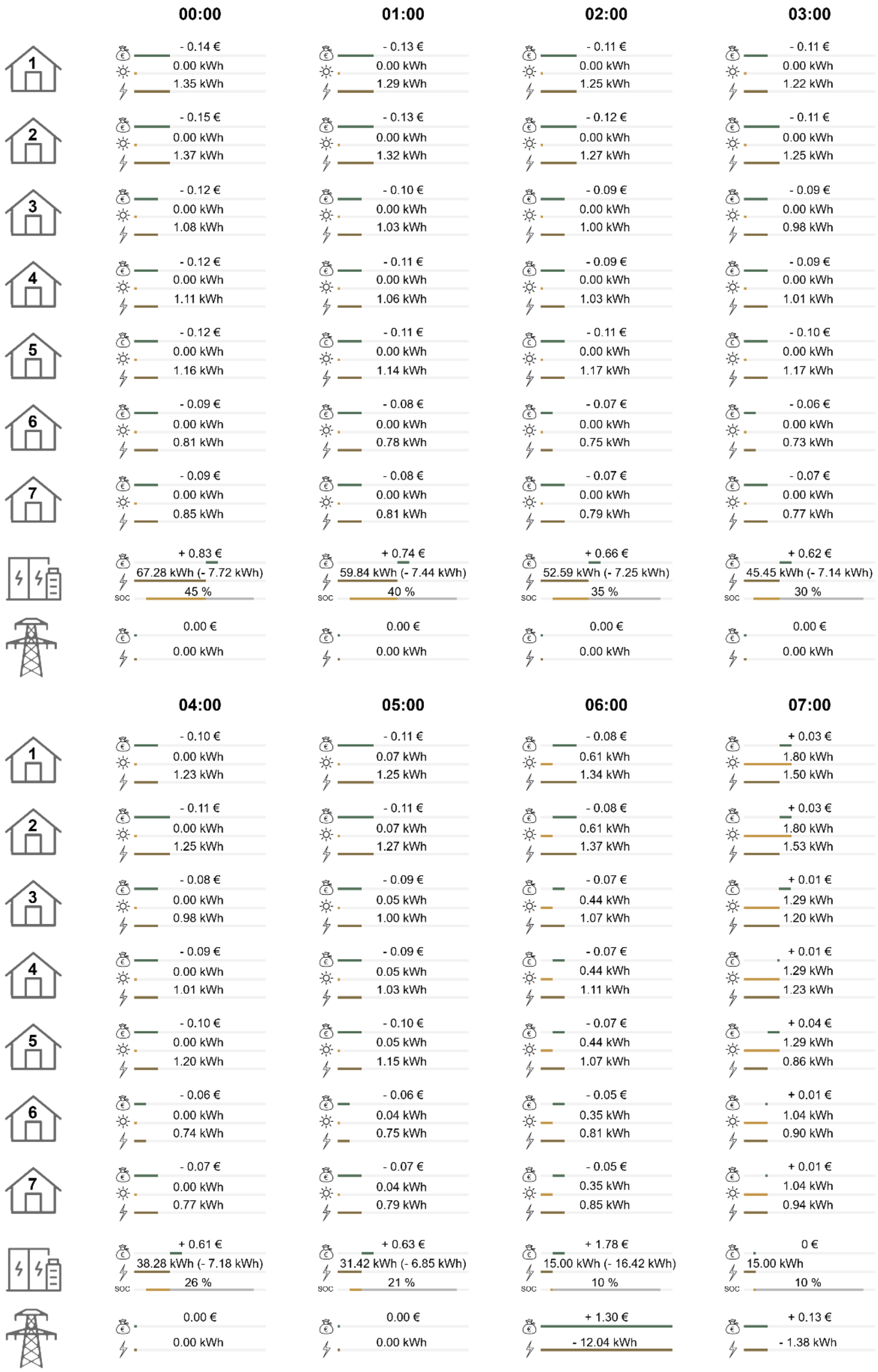

Figure 33. Distribution of Community Energy and Financial Flows (00:00 - 08:00)

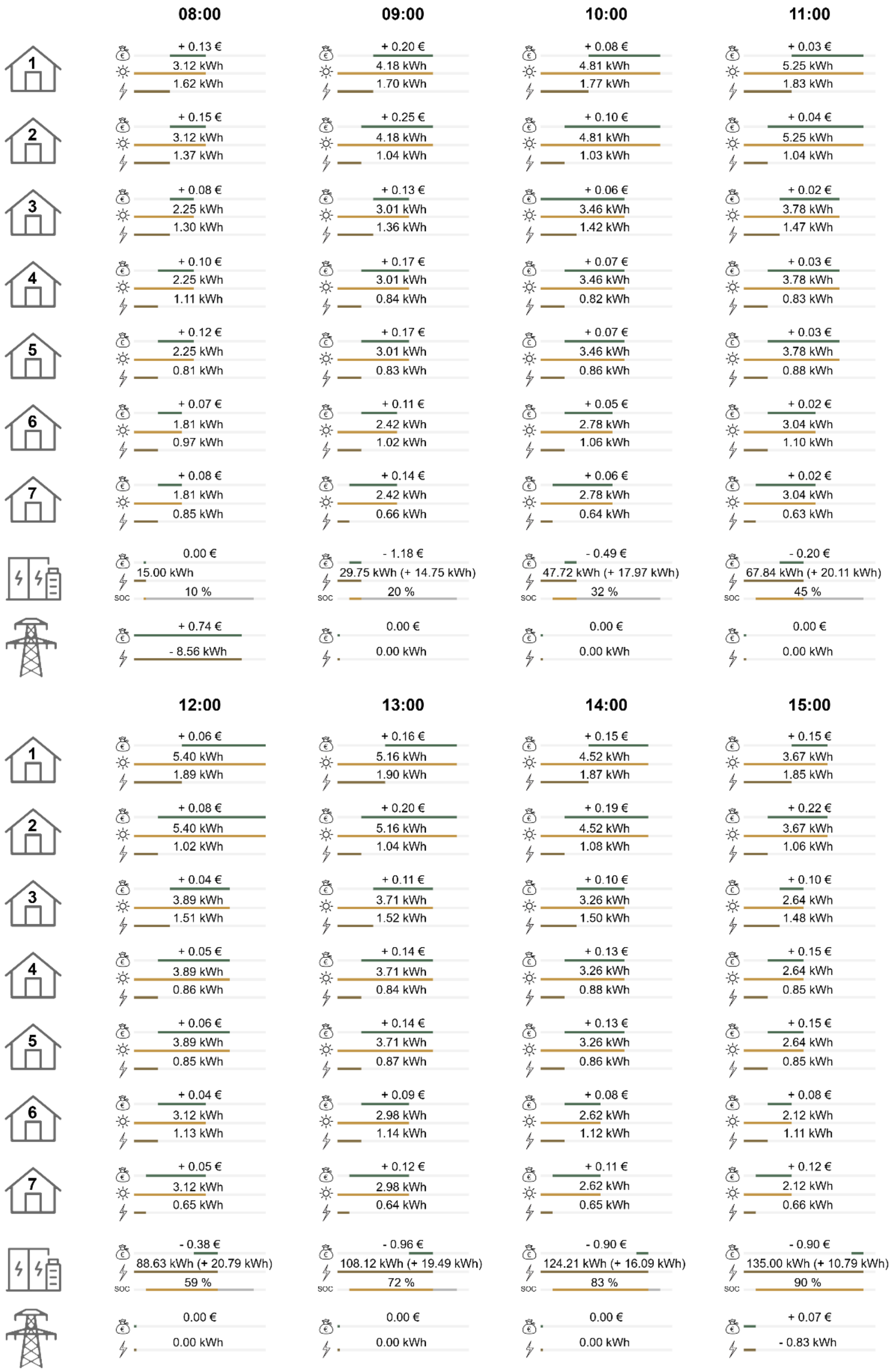

Figure 34. Distribution of Community Energy and Financial Flows (08:00 - 16:00)

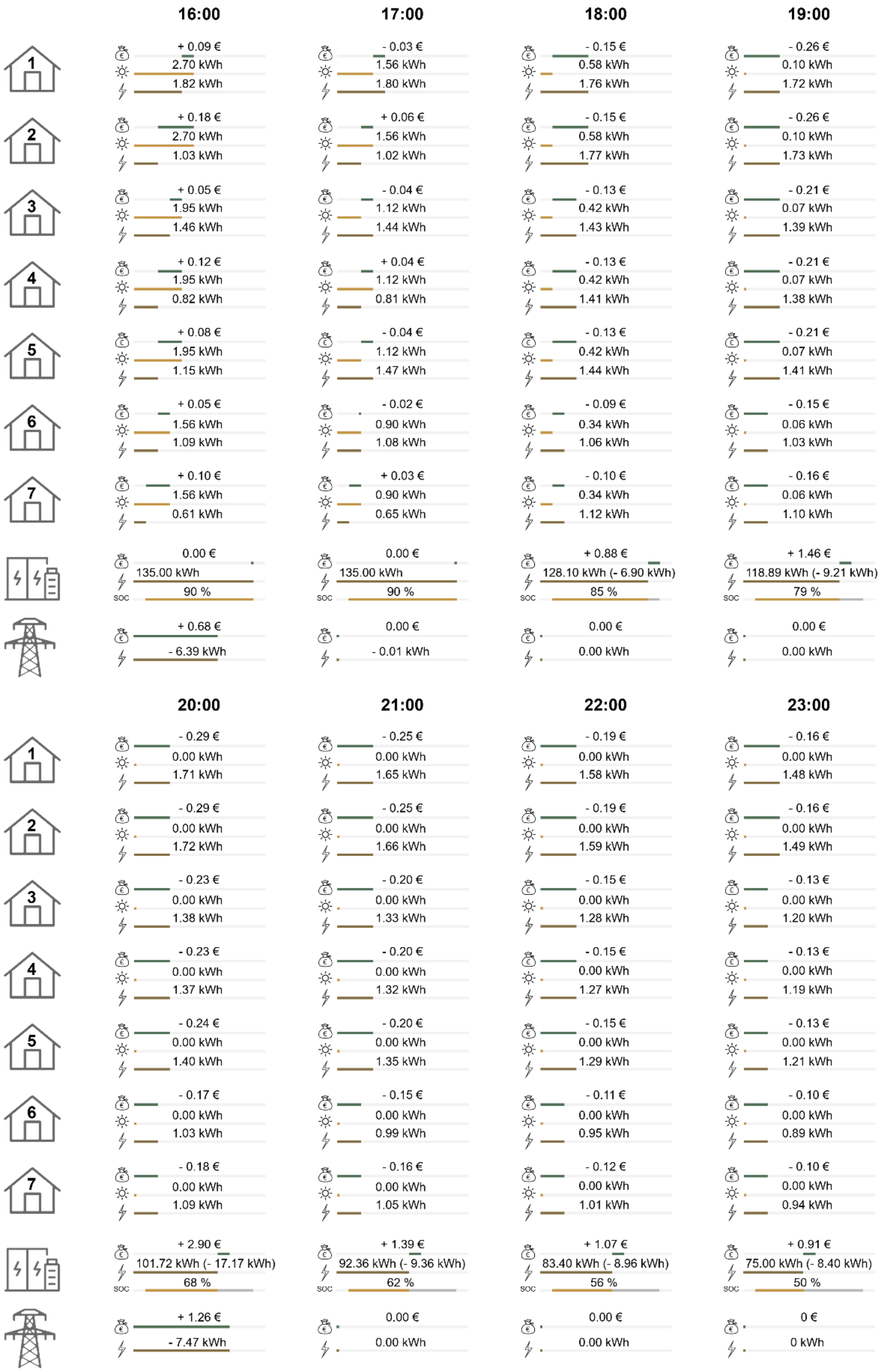

Figure 35. Distribution of Community Energy and Financial Flows (16:00 - 24:00)

5.2 Summary of Research Results

This research successfully developed a conceptual design, software architecture, and rule-based control algorithms for a cloud-based digital twin system applied to a microgrid-based renewable energy community. By integrating the physical data within a multi-layered digital domain, the developed framework transitions from a standalone BIM model into a data-driven optimization tool. The proposed EMS, formalized as a Python-based algorithm, targets Level 5 autonomous operation by enabling bidirectional data orchestration and automated decision-making without direct human intervention. To validate the functional logic and economic efficacy of this core EMS component, an operational simulation was executed in Section 5.1, confirming the viability of the developed control strategies.

The core findings and practical outcomes of this thesis are summarized as follows:

Established an energy community framework: Analysis of the Greek energy context confirmed the viability of PV-based renewable energy communities and demonstrated the technical and economic importance of BESS integration. The framework models a seven-house microgrid as a LES and establishes the sizing methodology for its core components.

Developed a multi-level digital twin architecture: A cloud-based digital twin architecture was designed, integrating BIM, IoT, forecasting, market, sizing, and EMS functions. The platform is designed to operate as a tertiary control layer, enabling strategic optimization while maintaining interoperability with primary and secondary microgrid controls.

Validated rule-based EMS control strategies: Rule-based dispatch and battery management algorithms were developed and validated to optimize self-consumption, surplus distribution, load balancing, and energy arbitrage. The system continuously adjusts energy flows in 15-minute intervals and translates optimization results into executable battery control actions.

5.3 Research Limitations and Future Perspectives

While this research establishes a comprehensive digital twin architecture and develops the operational logic of the EMS, several limitations should be acknowledged. The proposed framework remains primarily a conceptual and architectural implementation and has not been validated through a full-scale hardware deployment. Practical challenges related to device interoperability, sensor inaccuracies, and inverter integration therefore remain outside the scope of this study.

Furthermore, the architecture relies on cloud-based infrastructure, making its operation dependent on communication network availability and potentially introducing latency in real-time control execution. In addition, cybersecurity, fault tolerance, and resilience aspects of the platform were not investigated and require dedicated analysis before practical deployment. Finally, although the framework is designed to support larger deployments, its scalability beyond the seven-house case study has not been empirically evaluated.

Despite these limitations, the developed framework establishes a solid foundation for future research and practical implementation. While the present study comprehensively addresses the digital twin architecture and the operational logic of the EMS, several components were intentionally developed at a foundational level to define their structural role within the overall ecosystem. In particular, the Market System, Forecast System, and Community Sizing System provide the necessary framework for future enhancement rather than fully mature implementations. Consequently, multiple opportunities remain for extending the platform's functionality and increasing the operational, economic, and technological capabilities of both the energy community and its digital twin ecosystem.

Market System Evolution: The current Market System calculates internal community tariffs by subtracting a self-consumption remuneration from the prevailing market price. Future developments could introduce dynamic pricing based on local supply and demand, supported by blockchain technology and contracts to automate P2P energy transactions.

Advanced Forecast System: The Forecast System currently relies on external macro-level datasets scaled to the community level to estimate day-ahead generation and demand. As operational data accumulates, localized ML models can be trained to improve forecasting accuracy and enhance optimization performance.

Sizing System Formalization: This thesis establishes the relationships between the Community Sizing System and other digital twin components while outlining a methodology for determining the optimal PV-to-BESS capacity ratio based on a target payback period. The detailed optimization algorithm remains a subject for future research.

Building Management Integration: Integrating a full-scale BMS with the digital twin would enable active demand-side management by aligning flexible house loads with real-time renewable generation. Such integration could coordinate the operation of BESS, thermal storage, and electric vehicles, while expanding the platform with monitoring and remote-control capabilities for smart home devices.

Macro-Level Scaling: The proposed framework can be extended beyond the seven-house case study to multi-family residential complexes and urban districts. In such deployments, the energy community digital twin could serve as an energy layer within higher-level CIM-based smart city models, supporting integrated urban energy planning.

In this context, the proposed framework demonstrates how digital twin technologies can support the transition toward autonomous, data-driven, and sustainable energy communities.

Use of Artificial Intelligence

During the preparation of this thesis, the author used AI tools, including ChatGPT and Google Gemini, to improve text clarity and readability through language refinement and paraphrasing, and to support the transformation of pseudo-code into Python implementations, code refactoring, and improvements in code reusability and modularity. All generated or modified code was manually verified by the author. The author of the thesis takes full responsibility for the content of the thesis and confirms that all analyses, interpretations, and conclusions were developed by the author.

Bibliography

[1] International Energy Agency: IEA, “Electricity 2026. Analysis and forecast to 2030,” 2026.

[2] Energy Transition Commission, “Energy productivity: Increasing efficiency in an expanded, electrified energy system,” 2025.

[3] C.-C. Li, S. McArthur and S.-J. Lee, “Smart Grid Handbook,” *John Wiley & Sons Ltd.,* vol. 1, pp. 41-54, pp. 117-132, pp. 245-264, pp. 473-488, 2016.

[4] P. Kotsampopoulos, N. Hatziargyriou, S. Maiti, S. B. Karanki, C. N. Sorensen, et al., “Renewable energy empowering remote communities through microgrids: Control and management strategies to provide sustainable and cost-effective electricity,” *IEEE Electrification Magazine*, vol. 13, no. 2, pp. 37-48, 2025.

[5] C. Rani, P. Bhambri, A. Kataria, A. Khang, and A. K. Sivaraman, “Big Data, Cloud Computing and IoT,” *CRC Press*, pp. 1-29, pp. 65-80, pp. 181-200, 2023.

[6] A. Hussain, G. Tyagi, and S.-L. Peng, “IoT and AI Technologies for Sustainable Living,” *CRC Press*, pp. 57-78, 2023.

[7] C.-C. Li, S. McArthur and S.-J. Lee, “Smart Grid Handbook,” *John Wiley & Sons Ltd.,* vol. 2, pp. 563-618, pp. 727-745, 2016.

[8] A. Buonomano, C. Forzano, G. F. Giuzio, R. Maka, A. Palombo, et al., “Optimising renewable energy community aggregation for urban districts decarbonisation,” *Renewable and Sustainable Energy Reviews*, vol. 226, 2026.

[9] R. Sepehrzad, M. Yadav, G. C. Lazaroiu, I.-I. Avramidis, I. B. Benitez, et al., “A critical overview of local energy communities: State-of-the-art, real-life applications & challenges and tackling the academia-industry gap,” *Renewable and Sustainable Energy Reviews*, vol. 226, 2026.

[10] J Momoh, “Smart Grid. Fundamentals of Design and Analysis,” *IEEE Press*, pp. 1-27, pp. 140-159, 2012.

[11] F. Andrade, J. D. Vasquez-Plaza, A. Luna, M. Castro-Sitiriche, A. Irrizary, et al., “Microgrids for Resilience: Powering Puerto Rico’s Future: The Role of Community Microgrids in Improving Resiliency for Puerto Rico’s Remote Areas,” *IEEE Electrification Magazine*, vol. 13, no. 2, pp. 26–36, 2025.

[12] Y. Li, Z. Wang, H. Li, S. Maharjan, K. Kudart, et al., “Remote Islanded Microgrid: A Feasible and Economical Solution for Providing Resilience and Reliability to Power Systems in Rural Areas,” *IEEE Electrification Magazine*, vol. 13, no. 2, pp. 16–25, 2025.
[13] C.-C. Li, S. McArthur and S.-J. Lee, “Smart Grid Handbook,” *John Wiley & Sons Ltd.,* vol. 3, pp. 1133-1158, 2016.
[14] Thumann, T. Niehus, & W. J. Younger, “Handbook of Energy Audits,” *Fairmont Press*, 2013.
[15] Vihreä Energia, “Electricity 1.0.1 in Finland, https://vihreaenergia.fi/en/artikkelit/electricity-1-0-1-in-finland,” *Vihreä Energia*, 2026.
[16] Rajratnakharat, V. Bavane, V. Bavane, S. Jadhao, and R. V. Marode, “Digital Twin: Manufacturing Excellence through Virtual Factory Replication,” *NC-RACE 18*, 2018.
[17] McKinsey & Company, “What is digital-twin technology?” *McKinsey Explainers*, 2024.
[18] E. Glaessgen and D. Stargel, “The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles,” *ASC Structures, Structural Dynamics and Materials Conference 20th AIAA*, 2012.
[19] A. Fuller, Z. Fan, C. Day, and C. Barlow, “Digital Twin: Enabling Technologies, Challenges and Open Research,” *IEEE Access*, 2020.
[20] B. Metcalfe, H. C. Boshuizen, J. Bulens, and J. Koehors, “Digital Twin Maturity Levels: A Theoretical Framework for Defining Capabilities and Goals in the Life and Environmental Sciences,” *F1000Research*, 2023.
[21] Microsoft, “Microsoft Azure,” https://azure.microsoft.com/, 2026.
[22] Siemens, “Siemens Xcelerator,” https://www.siemens.com/en-us/company/digital-transformation/, 2026.
[23] A. Gilchrist, “Industry 4.0: The Industrial Internet of Things,” *Apress*, pp. 1–12, pp. 33–64, pp. 87–118, pp. 161–177, pp. 87–118, 2016.
[24] Autodesk, “Building Information Modeling in Practice,” *Autodesk Building Solutions*, 2002.
[25] A. Revoltia, L. Gualtieria, P. Pauwels, and P. Dallasega, “From Building Information Modeling to Construction Digital Twin: A Conceptual Framework,” *Production & Manufacturing Research*, 2024.
[26] Autodesk, “Autodesk,” https://www.autodesk.com/, 2026.

[27] W. Yu, X. Zhou, D. Wang, and J. Dong, “The Development and Construction of City Information Modeling (CIM): A Survey from Data Perspective,” *Applied Sciences*, 2025.
[28] R. Khallaf, C. J. Anumba, G. Castelblanco, and M. Hastak, “Smart City Digital Twin: A System-of-Systems Approach,” *CIB Conferences*, 2025.
[29] World Economic Forum, “Digital Twin Cities: Key Insights and Recommendations,” *World Economic Forum*, 2023.
[30] Esri, “ArcGIS,” https://www.esri.com/, 2026.
[31] Bentley, “Bentley Systems,” https://www.bentley.com/, 2026.
[32] Unreal Engine, “Unreal Engine,” https://www.unrealengine.com/, 2026.
[33] Unity, “Unity,” https://unity.com/, 2026
[34] Autodesk, “Levels of Development in BIM: Enabling coordination and collaboration,” https://www.autodesk.com/solutions/bim-levels-of-development, 2026.
[35] M. S. Bonney, M. de Angelis, M. D. Borgo, and D. J. Wagg, “Development of a Digital Twin Operational Platform Using Python Flask,” *Data Centric Engineering*, 2022.
[36] W. Hu, T. Zhang, X. Deng, and J. Tan, “Digital Twin: A State-of-the-art Review of its Enabling Technologies, Applications and Challenges,” *Journal of Intelligent Manufacturing and Special Equipment*, 2021.
[37] F. Tao, X. Sun, J. Cheng, and X. Jin, “Maketwin: A Reference Architecture for Digital Twin Software Platform,” *Chinese Journal of Aeronautics*, 2023.
[38] H. Wu, P. Ji, H. Ma, and L. Xing, “A Comprehensive Review of Digital Twin from the Perspective of Total Process: Data, Models, Networks and Applications,” *Sensors*, 2023.
[39] R. Buyya and A. V. Dastjerdi, “Internet of Things: Principles and Paradigms,” *Elsevier Inc.*, pp. 3-27, 2016.
[40] T. Erl, W. Khattak, and P. Buhler, “Big Data Fundamentals: Concepts, Drivers & Techniques,” *Arcitura Education Inc.*, 2016.
[41] M. Copeland, J. Soh, A. Puca, M. Manning, and D. Gollob, “Microsoft Azure: Planning, Deploying, and Managing Your Data Center in the Cloud,” *Apress*, pp. 1-26, 2015.
[42] F. Hu, “Big Data: Storage, Sharing, and Security,” *CRC Press*, pp. 15-41, 2016.
[43] B. Azarmi, “Scalable Big Data Architecture,” pp. 17-55, *Apress*, 2016.
[44] R. Stackowiak, A. Licht, V. Mantha, and L. Nagode, “Big Data and the Internet of Things: Enterprise Information Architecture for a New Age,” Apress, 201