A framework for the digital energy management and decarbonization of sustainable and renewable energy communities

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Abstract. The increasing complexity of energy systems at the community scale, both in urban and rural contexts, requires advanced digital tools capable of supporting data integration, simulation, and optimization. This contribution proposes a sequential framework that evolves from a digital model, dedicated to the collection, interoperability, and normalization of energy data, to a full Digital Twin (DT), which integrates predictive models, optimization algorithms, and advanced control for the coordinated management of sustainable urban and rural communities. The proposed framework is conceived as a methodological structure applicable to different types of sustainable urban and rural communities. Within this broad scope, Renewable Energy Communities (RECs) are adopted as a paradigmatic application case. RECs represent a particularly suitable example due to their clear regulatory definition, structured incentive mechanisms, and explicit focus on collective renewable energy management, which make them an ideal testbed for advanced digital solutions. The framework addresses multiple planning and operational functions, including energy optimization, scenario-based simulation, predictive maintenance, and the management of demand- and supply-side flexibility. It enables increased integration of renewable sources, reduction of peak loads, improvement of local grid performance, and support for decarbonization strategies in both urban and rural environments. The proposed approach provides a unified methodological structure to guide the transition from simple digital tools to full-fledged urban DTs capable of supporting operational and planning decisions in smart cities.

1 Introduction

The built environment is one of the most energy-intensive sectors, accounting for 40% of global energy use and 33% of CO_2 emissions, highlighting the need for more sustainable urban design and management (United Nations Environment Programme, 2024). With the 2030 Agenda for Sustainable Development, the United Nations emphasized the importance of reducing energy consumption and improving urban living standards through Sustainable Development Goal (SDG) 11: "Sustainable cities and communities".

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At the European level, the European Green Deal [2] and the European Climate Law [3] legally commit the EU to achieving climate neutrality by 2050. To reach this goal, the Clean Energy for All Europeans Package (CEP) promotes a paradigm shift toward decentralized energy systems and active citizen participation. Within this context, Renewable Energy Communities (RECs) have emerged as the paradigmatic example of sustainable urban and rural communities. RECs are explicitly defined, regulated, and incentivized by the Renewable Energy Directive (RED II) [4]. Specifically in Italy, RECs were first introduced by the "Milleproroghe" decree [5], while the 2024 law from the Ministry of the Environment and Energy Security [6] established their regulatory and incentive framework.

RECs empower citizens, businesses, and institutions to jointly produce and share renewable energy, promoting self-sufficiency and delivering environmental, social, and economic benefits [7]. They represent local, self-organized systems where consumers can also act as producers (called prosumers), contributing to a decentralized and digitalized energy landscape [8]. While these models are being implemented also in Italy, small municipalities and rural areas still face technical and administrative challenges due to limited financial resources and a lack of dedicated technical staff. Therefore, developing methodologies and digital tools to support them in the design and management of these communities is essential [9].

The growing interest in RECs reflects a wider transformation of the energy sector toward decentralization, decarbonization, and citizen participation [10]. RECs represent a cornerstone of this transition, enabling local actors to jointly produce, consume, and manage renewable energy while fostering social inclusion and economic sustainability [11]. However, the existing literature reveals that the methodological and technological frameworks supporting RECs implementation remain fragmented and insufficiently integrated. Current approaches often treat technical, economic, and social dimensions of RECs as separate layers, hindering interoperability, scalability, and user empowerment [12].

This research addresses this gap by developing an integrated framework that structures REC analysis across all key phases: from defining boundaries and roles to generating input data, simulating energy flows, evaluating flexibility potential, and validating results through real or synthetic datasets. From the outset, the digital model is conceived to support several core applications: REC dimensioning, optimisation of internal energy exchanges, assessment of flexibility provision and participation in relevant markets. These uses guide the methodological structure and ensure that the framework responds to both technical and operational needs of real communities. Within this structured approach, the project advances the development of a digital model that operationalizes the framework, aggregates input data, and enables the assessment of alternative REC configurations [13]. Through the integration of automated input data updates, this model provides the necessary infrastructure for a full Digital Twin (DT) [14], designed for predictive simulations and operational dynamic optimisation. In the long term, these advancements would enhance energy management, flexibility forecasting, and participatory governance, enabling community members and institutions to make more informed operational, investment, and policy decisions.

The originality of this work lies in unifying technical, economic, and sustainability dimensions within a single digital framework, overcoming the fragmentation observed in current sustainable community tools [15]. While the proposed methodology is applicable to the broader category of sustainable urban and rural communities, this study specifically adopts RECs as a reference model. This choice allows for the validation of the framework within a regulated and incentivized context, contributing a replicable, transparent, and user-oriented basis for planning and managing these systems throughout their full life cycle. Moreover, this provides the energy sector with a practical basis for coordinating decentralized generation, enhancing grid resilience, and informing sustainable energy policies. Through the design and implementation of this DT, the research seeks to advance both the scientific understanding and the practical deployment of RECs as resilient, participatory, and business models of collective energy ownership.

2 Methodology

The methodological framework developed for the construction of DTs to support the energy management and decarbonization of sustainable urban and rural communities, such as RECs, is structured as a comprehensive, multi-layered process shown in Figure 1. This framework is explicitly designed to bridge the gap between theoretical energy modelling and real-time operational optimization. The methodology is segmented into three distinct chronological and functional phases: the Modelling phase, the Construction phase, and the Operating phase. This tripartite structure ensures that the digital model evolves from a simulation environment into a dynamic, adaptive system capable of interacting with physical assets. The integration of these phases allows for a seamless transition from planning and dimensioning to active management and continuous improvement, facilitated by advanced computational architectures and feedback loops.

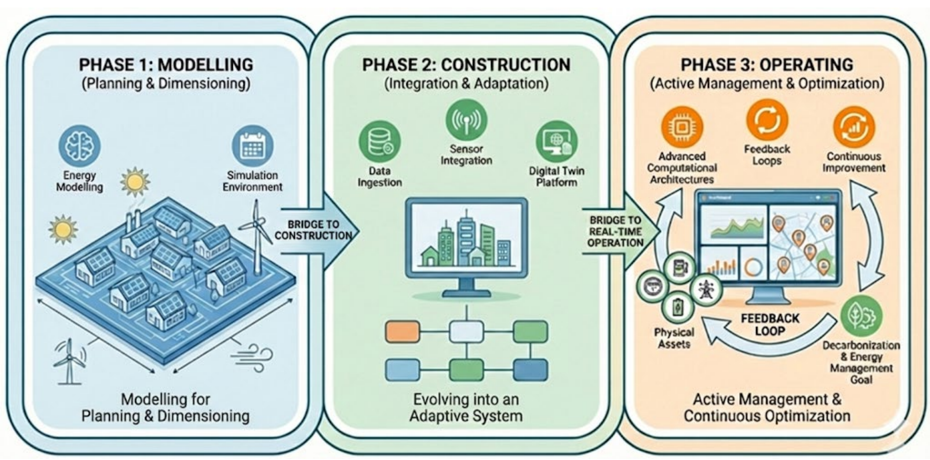

Fig. 1. Schematic representation of the proposed DT framework. The diagram illustrates the chronological progression through three distinct phases.

2.1 Phase I: The Digital Modelling and Simulation Phase

The Modelling Phase serves as the foundational bedrock of the DT, focusing on the rigorous characterization and simulation of the REC's potential performance prior to physical implementation. This phase is characterized by a series of modules shown in Figure 2 that address social, technical, economic, and environmental dimensions.

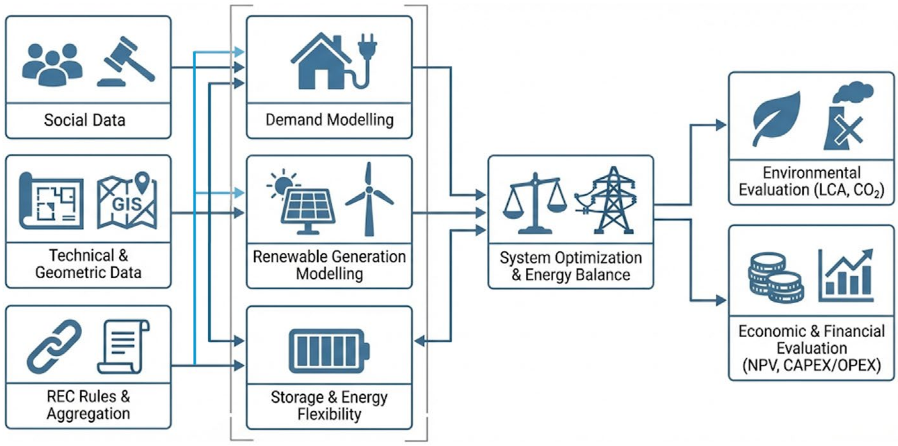

Fig. 2. Workflow of the Modelling Phase showing the different interconnected modules (a connection is rendered in light blue for sake of legibility)

The initial phase involves the Social Data Module, which is critical for defining the non-technical boundary conditions of the community. This module is responsible for the identification of vulnerable users and the establishment of baseline energy poverty indicators. To achieve this, the methodology employs a qualitative approach, analysing sociological data to map the community's demographic structure. This qualitative assessment ensures that the subsequent technical designs are sensitive to the specific needs of the community members, particularly regarding inclusivity and social equity. Following the social characterization, the framework proceeds to the Technical & Geometric Data Module, designed to systematically parse and analyse complex building and roof geometries. By leveraging high-resolution spatial data, the module extracts morphological parameters, such as roof pitch, azimuth, and surface area, while accounting for geometric irregularities and shading obstructions.

In parallel to the previous modules, the framework continues to the REC Rules and Aggregation Module. This step translates the regulatory and social structures into computational logic, implementing REC-specific rules such as user aggregation, shared energy calculations, and incentive eligibility. To handle the complexity of diverse user profiles, the literature suggests the use of advanced segmentation strategies, such as unsupervised clustering algorithms. These approaches allow for the categorization of users based on consumption patterns and other relevant attributes, facilitating optimized aggregation strategies that maximize the collective benefits of the community.

The core technical simulations begin with Demand Modelling Module. This module simulates the energy demand for all REC members, which may include households, Small and Medium Enterprises (SMEs), and public buildings. The framework allows for flexibility in data sources, utilizing either synthetic load profile generators or statistical data to construct accurate temporal consumption profiles. This step is crucial for establishing the baseline load requirements that the renewable energy systems must meet.

Parallel to demand modelling, the Renewable Generation Modelling Module simulates local renewable energy production. This simulation is supported by the Technical & Geometric Data Module, which analyses building and roof geometries. The geometric data feeds into industry-standard energy simulation software such as TRNSYS, or Energy PLAN. These tools calculate the potential energy generation based on local weather data, system efficiency, and losses.

To address the intermittency of renewable generation and manage the community's adaptive capacity, the Storage and Energy Flexibility Module is employed. This module models system flexibility from two distinct perspectives: a technical standpoint, utilizing electrochemical and/or thermal storage systems, and a regulatory standpoint, implementing demand response mechanisms. This module determines optimal charging and discharging cycles to maximize self-consumption and ensure grid stability while integrating logic against specific constraints. Simultaneously, regarding the regulatory aspect, the module integrates management. To ensure responsiveness, the framework envisions the use of adaptive control algorithms capable of dynamically coordinating both physical storage assets and demand response strategies. With this approach it is possible to reduce stress on the grid and maximize the utilization of local renewable resources.

The integration of demand, generation, and storage is managed by the System Optimization and Energy Balance Module. This component solves the hourly energy balance across the system boundary, accounting for demand, generation, and grid import/export flows. To address the complexity of balancing conflicting flows, the framework envisions the application of algorithmic solutions capable of handling trade-offs. Techniques such as Multi-Objective Optimization (MOO) represent a valid reference point in the literature for solving these types of multi-variable problems. This ensures that the system not only meets energy needs but does so in a way that balances cost, reliability, and grid interaction.

The Modelling Phase concludes with evaluation modules. The Environmental Evaluation Module quantifies Carbon Dioxide (CO_2) emissions across the entire lifecycle of the system through Life Cycle Assessment (LCA) and seeks to minimize them. Concurrently, the Economic and Financial Evaluation Module performs a simplified analysis of Capital Expenditures (CAPEX) and Operational Expenditures (OPEX), quantifying cash flows to ensure financial viability.

2.2 Phase II: The Construction Phase

Transitioning from simulation to implementation, the Construction Phase focuses on defining the physical and digital infrastructure required for DT. The primary objective of this phase is Operational Data Acquisition, which involves the collection of real operational data from the installed assets. This data is intended to serve as the "ground truth" for DT.

To manage the high volume and velocity of data generated by the REC, the framework proposes the adoption of advanced data integration architectures. These systems are designed to unify heterogeneous data sources by utilizing semantic mediators to ensure interoperability. Structurally, the architecture is modelled on a Cloud-Edge continuum, distributing computational tasks across the network. In this envisioned setup, Edge computing would handle immediate data processing at the source (e.g., smart meters, inverters), fog computing would provide intermediate aggregation and analysis, and cloud computing would manage long-term storage and heavy-duty processing. This approach, shown in Figure 3, aims to ensure low latency, high reliability, and scalability, which are essential for real-time energy management.

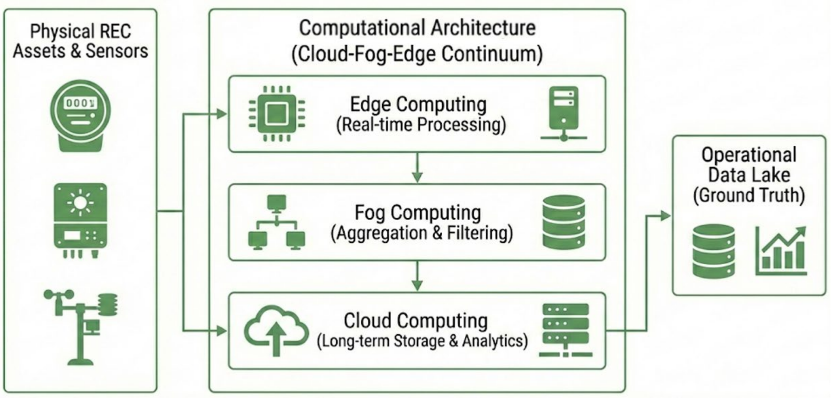

Fig. 3. Workflow of the Construction Phase showing the different interconnected modules

2.3 Phase III: The Operating Phase

The Operating Phase represents the active life of the DT, where the focus shifts to validation, maintenance, and continuous optimization. This phase, shown in Figure 4, is governed by a cyclical process of monitoring and recalibration.

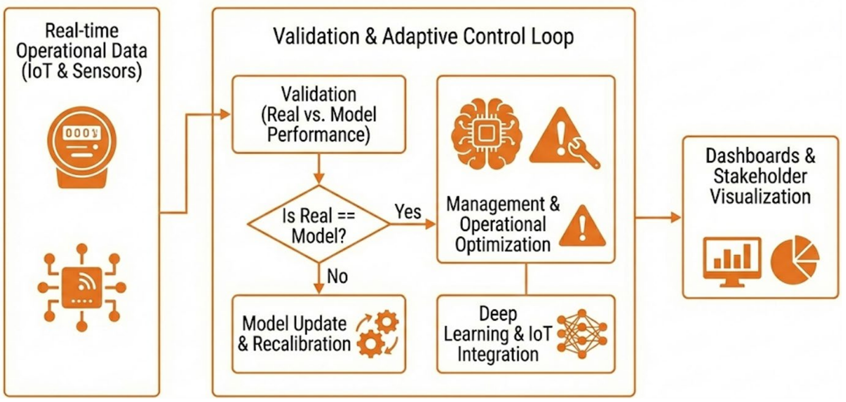

Fig. 4. Workflow of the Operating Phase showing the different interconnected modules

The central mechanism of this phase is the Validation and Control Loop. The system continuously compares the real-time operational data against the optimal performance predicted by the models in Phase I. This comparison assesses whether the physical system's performance is equal or not to the digital benchmark. If the performance metrics do not align, indicating a discrepancy between the model and reality, the system triggers a Model Update and Recalibration process. This process updates the demand, generation, and dispatch models based on the measured data, effectively "teaching" the DT to better reflect current realities. This may also trigger a re-evaluation of the environmental impact using LCA methodologies to ensure emission targets remain within range.

When the validation process confirms that the system is performing as expected, the framework proceeds to Management and Operational Optimization. This module is responsible for the continuous performance monitoring and adaptive operation of the REC. It relies on a suite of advanced IoT devices integrated with machine learning algorithms. These technologies work together to facilitate detection for deviations and inefficiencies, identifying potential faults before they escalate.

The optimization logic may be further enhanced by real-time deep learning techniques integrated directly with the IoT infrastructure. These deep learning models enable the system to learn from historical data patterns, predicting future states and automating complex decision-making processes. If significant deviations or new opportunities for expansion are detected, the system can trigger a model recalibration or signal the need for system expansion.

Finally, to ensure transparency and support human decision-making, all operational data, financial metrics (such as Net Present Value, Payback Period, IRR and others), and performance indicators are visualized through dashboards or digital platforms. These dashboards provide stakeholders with an intuitive interface to monitor the REC's status, verifying economic parameters like energy bill reductions and dedicated withdrawal rates. This visualization layer completes the DT framework, transforming complex data streams into actionable insights for sustainable management of RECs. This interface operationalizes the proposed unified approach, explicitly overcoming the fragmentation of existing tools by integrating technical, economic, and sustainability metrics into a single, cohesive decision-support environment.

3 Implementation of technical and geometric data module

The selected case study for the validation of the proposed DT framework is the *Comune di Lecco*, an urban centre located in the Lombardy region of Northern Italy.
The city has actively pursued decarbonization strategies by spearheading the establishment of a REC, officially denominated as CERS Lecco (*Comunità Energetica Rinnovabile e Solidale di Lecco*).

Currently, the proposed framework is in the process of implementation within this case study where the district analysed constitutes the actual cluster of buildings where the REC will be physically realized. Specifically, this research presents the deployment of the Technical and Geometric Data Module, as detailed in the following paragraph. The output generated by this module establishes the structural foundation required to build the energy model and integrate the subsequent optimization components, laying the groundwork for the complete implementation of the DT framework.

3.1 Data Acquisition

To establish the physical boundary conditions of the digital model, the research utilized high-resolution Light Detection and Ranging (LIDAR) dataset from the *Comune di Lecco*. However, the utilization of this municipal dataset presented significant technical challenges inherent to raw remote sensing data. The LIDAR point clouds were provided in a raw, unclassified format, which introduced significant complexities in semantic segmentation. Specifically, the automated distinction between dense vegetation and building structures proved particularly arduous, as the elevation profiles often overlapped in areas with high canopy cover or green roofing. Furthermore, critical radiative properties such as surface albedo, which are indispensable for accurately simulating reflected irradiance in the subsequent photovoltaic generation models, were absent from the dataset metadata. Consequently, these values required derivative estimation based on surface type assumptions; this approximation introduces a margin of uncertainty and is acknowledged as a limitation of the current model's precision.

3.2 LIDAR Classification

The computational magnitude of the dataset, fragmented into 18 distinct patches of approximately 16 million points each, imposed severe constraints that necessitated a trial-and-error search for a computationally efficient classification workflow. Initial attempts utilizing standard commercial geoprocessing software, such as CloudCompare and ArcGIS Pro, proved unfeasible; the GUI overhead saturated workstation RAM, leading to system instability, while the lack of native batch-processing capabilities prevented the automation required for such a large dataset. Similarly, state-of-the-art deep learning architectures like RandLA-Net were discarded because the raw municipal data lacked critical radiometric channels (specifically albedo and intensity), preventing the neural network from distinguishing between spectrally similar features like flat roofs and dense ground vegetation. Unsupervised clustering algorithms were also evaluated to automate segmentation based on spatial density; however, the quadratic memory complexity required for distance matrix calculations consistently triggered "Out of Memory" (OOM) exceptions, rendering them incompatible with the available hardware infrastructure.

Consequently, a custom deterministic geometric algorithm was implemented as the optimal solution. Utilizing explicit logic gates based on physical terrain properties, the script applied geometric constraints, including height thresholds, normal variance, and planarity checks, to distinguish the stochastic vertical scatter of vegetation from the planar consistency of rooftops. Operating with linear time complexity, the algorithm processed points sequentially, drastically reducing the memory footprint to enable the rapid computation of the 18 massive data patches without system saturation. This approach successfully generated the clean, classified LIDAR points required for the subsequent 3D model, as illustrated in Figure 5.

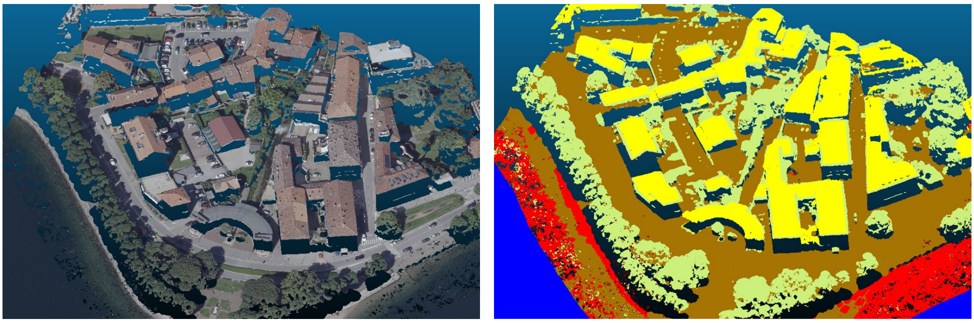

Fig. 5. Comparative visualization of one of the LIDAR datasets for the Comune of Lecco. On the left: Raw, unclassified point cloud. On the right: Result of the geometric classification algorithm, showing the successful segmentation of buildings (yellow), vegetation (green), ground terrain (brown), noise (red) and water (blue).

3.3 3D Model Reconstruction and Simplification

Following the successful semantic classification of the point clouds, the subsequent imperative was to convert the discrete geometric data into a continuous 3D model suitable for energy simulation. The objective was to generate a Level of Detail (LOD) model capable of representing building volumes and roof orientations with sufficient accuracy for irradiation calculations.

Initial attempts using ArcGIS proved operationally deficient due to the need for excessive manual roof rectification and the inability to handle the dataset's fragmentation. Memory constraints prevented the seamless merging of the 18 distinct patches, resulting in "cut" building geometries at boundaries that would invalidate the subsequent energy analysis.

To resolve these scalability and topological continuity issues, the research adopted City4CFD, an open-source reconstruction tool. This computational framework is specifically engineered to handle large-scale urban datasets and automate the generation of watertight 3D city models. Unlike the manual constraints of standard GIS tools, City4CFD offered a robust, automated pipeline capable of processing the aggregate dataset. It effectively resolved the boundary discontinuities by treating the geometry globally rather than locally, ensuring that buildings straddling patch divisions were reconstructed as coherent, single entities. This shift to an automated, code-based reconstruction method was decisive in generating a topologically valid 3D model of the *Comune di Lecco* without the need for prohibitive manual correction.

Finally, to ensure the highest geometric fidelity before simulation, the output model was imported into Blender. This open-source 3D creation suite served as a final quality control stage, allowing for the manual inspection and refinement of complex architectural features that automated algorithms might oversimplify. This reconstructed and refined three-dimensional model constitutes the indispensable geometric foundation upon which the DT of the CERS Lecco will be erected, providing the spatial accuracy required to populate the system with energy, social, and economic data in the subsequent phases of the framework.

Fig. 6. Final 3D model of the case study buildings from Blender software

4 CONCLUSIONS

This research proposes a novel, multi-layered framework for the construction of Digital Twins (DT) designed to support the decarbonization of sustainable urban and rural communities such as RECs. By structuring the DT lifecycle into Modelling, Construction, and Operating phases, the methodology bridges the critical gap between theoretical planning and adaptive, real-time management. A key innovation lies in the holistic integration of socio-economic indicators alongside technical simulations, ensuring that the digital model reflects the complex reality of RECs. Furthermore, the inclusion of a rigorous Validation and Recalibration Loop ensures continuous synchronization between physical and digital assets, utilizing IoT and Cloud-Fog-Edge architectures to enable self-optimizing control strategies.

The preliminary application of this framework to the *Comune di Lecco* validated the Technical and Geometric Data Module, successfully converting raw municipal LIDAR data into a robust 3D geometric foundation, despite significant computational challenges. Ultimately, this framework provides a scalable and replicable roadmap for the digitalization of energy systems, transforming energy models into dynamic, autonomous tools capable of driving efficient community management and achieving long-term sustainability goals.

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