GameL: a Neuro-Symbolic Agentic Architecture Toward Autonomous and Resilient Energy Communities

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Abstract

Energy dependence on fossil fuels represents one of the most critical vulnerabilities of modern societies, exposing them to persistent instability and precarious supply conditions, as geopolitical crises have demonstrated. Italy exemplifies this vulnerability, as the vast majority of its energy consumption relies on fossil fuel imports. Efficient, competitive, and sovereign alternatives are therefore increasingly urgent. Fortunately renewable sources are today generating a growing and geographically distributed supply of clean energy. If properly orchestrated this diversified grid can mitigate, and ultimately resolve, the dependence created by fossil fuel imports. This paper presents GameL, an ongoing research project proposing an intelligent decision-support platform for energy communities, built on Agentic Neuro-Symbolic Artificial Intelligence. GameL aims to foster energy independence by reducing reliance on external supply and empowering users who both produce and consume energy (prosumers) to actively govern their own energy flows. To this end, each energy asset in the community is modeled as a proactive agent negotiating energy flows in real time through explainable, formally reasoned decisions. The system is designed to be resilient, instantly redirecting surplus energy toward those who need it, and efficient, anticipating demand to minimize dispersion.

Keywords

Green AI, Neuro-Symbolic AI, Agentic AI, Smart Energy Grid

1. Introduction

Energy dependence on fossil fuels is a critical vulnerability of modern societies, exposing national infrastructures to price volatility and supply disruptions, as recent geopolitical crises have shown [1]. The reshaping of European gas markets shows how inextricably energy security and geopolitical stability are intertwined, driving emergency interventions that could have been avoided through greater diversification of supply sources [2]. This issue is particularly evident in countries such as Italy, where a large share of energy consumption relies on imported fossil resources, making the system structurally dependent on external factors and limiting its strategic autonomy. Energy resilience, then, is as much a question of national security as it is of economics or environmental stewardship. In this context, renewable energy sources are reshaping the traditional structure of power generation. The rapid deployment of photovoltaic installations, wind farms, and storage systems over the past decade has fundamentally altered the topology of electrical networks, shifting the paradigm from a centralized, unidirectional model, in which large power plants dispatch energy toward passive consumers, to a decentralized, bidirectional one, in which prosumers simultaneously produce and consume electricity, feed surpluses back into the grid, and actively participate in balancing mechanisms [3, 4]. This transformation is reflected in the emergence of energy communities, cooperative frameworks

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in which neighborhoods share locally produced renewable energy, coordinate consumption patterns, and collectively pursue economic and environmental objectives.

However, the transition toward renewable energies introduces new challenges, such as a intermittent production, a highly dynamic demand, and the necessity to coordinate an increasing number of heterogeneous devices [5, 6]. The stochastic nature of solar and wind generation, combined with the growing electrification of heating, mobility, and industrial processes, creates complex imbalances that traditional grid management tools were not designed to handle. Without intelligent orchestration mechanisms, the potential of renewables to reduce fossil dependency risks being limited by inefficiencies, dispersion, and the inability to react to sudden imbalances. Addressing these challenges requires moving beyond purely reactive control strategies toward frameworks that are capable of anticipating critical conditions, reasoning about the collective behavior of multiple interacting agents, and providing formally verified guarantees of correct operation even under failure or stress scenarios.

Our Contribution. We introduce *GameL*, an ongoing research project aimed at developing an intelligent platform for energy communities focusing on the modelling of the system led by the authors of this work. The defining characteristic of the proposed framework is its *neuro-symbolic* architecture [7, 8], which integrates a data-driven neural component with a formally grounded symbolic reasoning layer, allowing the platform to combine the predictive power of machine learning with the verifiability and transparency of logic-based methods. On the neural side, each device in the community is continuously monitored through a node-indexed multivariate time series, and a short-term forecasting module predicts generation, load, and market signals over a horizon of up to one day ahead [9]. On the symbolic side, the energy community is formalized as a directed graph embedded, basically a modified Kripke Structure, where nodes represent devices and prosumers, edges encode energy flows, and the energy of each entity can be redirected depending on the current operational regime. Obstruction Logic (OL) [10] provides the formal backbone for reasoning over this structure. It selectively deactivates arcs that are non-essential, verifies optimal energy-flow strategies through polynomial-time model checking, and certifies that desired properties, such as the uninterrupted supply of critical nodes, are guaranteed under all admissible reconfigurations. When OL prescribes a strategy, a flow replanning module translates it into a physically feasible energy dispatch over the residual network, closing the loop between formal verification and operational execution. The cooperation between the modules ensures that the strategic decisions taken at the symbolic level remain consistent with, and accountable to, the predictive evidence produced by the neural component. By combining machine learning and strategic reasoning inspired by game theory, *GameL* aims to provide real-time recommendations that are not only efficient and adaptive, but also transparent, formally verified, and explainable to human operators.

Related Works. Energy communities and smart grids have been extensively studied as socio-technical systems for coordinating consumers and prosumers. Recent surveys highlight the need to jointly address modelling, business models, optimisation objectives, policy constraints, and multi-energy interactions [11], while the Italian Renewable Energy Community landscape remains shaped by evolving regulation and heterogeneous technical, legal, and socio-economic barriers [12]. In parallel, multi-agent systems have long been recognised as a suitable paradigm for modelling autonomous, situated, and socially interacting entities [13], and have been widely applied to smart-grid monitoring, control, interoperability, restoration, and fault-tolerant operation [14, 15]. Unlike approaches mainly focused on negotiation, distributed optimisation, rule-based control, or simulation, *GameL* combines a machine learning forecasting component with a formally verifiable game-theoretical abstraction, where objectives are defined via formal logic specifications expressing the satisfaction of properties by the entities in the system. This machine-learning component aligns with the broader adoption of Artificial Intelligence techniques for decision support in domains such as industrial systems [16], transportation [17], and healthcare [18, 19]. *GameL* adopts a decoupled neuro-symbolic design [20, 7, 21]: the neural component forecasts node-indexed multivariate time series, while the symbolic component reasons over a graph/game representation of the current community state informed by the predicted data. This separation combines statistical learning with explicit symbolic reasoning, aiming to improve data efficiency and trustworthiness. This symbolic side is based on formal strategic reasoning [22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39]. While Alternating-time Temporal Logic introduced coalition modalities over Concurrent Game Structures [22], Obstruction Logic [10, 40, 41] further extends this line of work by considering dynamic game models in which arcs can be selectively deactivated under grade constraints while retaining polynomial-time model checking. This makes it well suited for energy communities, where non-essential energy-flow arcs can be temporarily disabled and redirected to preserve critical services. *GameL* also connects to resilience-oriented microgrid and distribution-system research, where distributed energy resources, storage, flexible loads, and network reconfiguration support critical-load restoration after disturbances. Existing reviews identify cost minimisation and stability constraints as central dimensions of resilient operation [42], while optimization-based methods can restore prioritized loads under topological and operational constraints [43]. *GameL* complements these approaches: flow replanning still provides a physically feasible dispatch, but only after a symbolic obstruction step has identified which connections to disable and certified, at the strategic level, why the resulting reconfiguration preserves critical supply.

Outline. Section 2 sketches the *GameL* framework. Section 3 presents the dataset required to develop the predictive component. Section 4 focuses on the symbolic component. Section 5 concludes the paper.

2. High-Level Architecture

This section provides a comprehensive conceptual characterization of each constituent block of the proposed architecture, along with a description of the overall information flow that traverses the system. The architecture is designed around two primary objectives: the first objective concerns the *forecasting* of energy workflows throughout the day. More specifically, the system aims to anticipate periods in which it is most advantageous to charge storage batteries using energy produced from renewable sources by jointly considering both the expected generation profile and the dynamic pricing of energy on the market. Accurate forecasting in this domain requires the ability to model complex temporal dependencies and nonlinear relationships among heterogeneous variables, including meteorological conditions, consumption patterns, and market signals. The second objective pertains to the *intelligent redirection* of energy flows in response to critical situations. In such scenarios, the system must be capable of dynamically reallocating available energy in a safe and controlled manner, assigning priority to nodes of higher societal importance, such as hospitals, emergency services, or other critical infrastructure, while ensuring overall grid stability.

To fulfill the forecasting objective, the first architectural component is responsible for processing large volumes of heterogeneous data and producing reliable predictions. This role is naturally suited to *neural networks*, which currently constitute the backbone of most modern automated analytics and predictive technologies. The success of neural networks in such domains is largely attributable to their capacity to learn complex, nonlinear representations from large-scale datasets, enabling strong generalization across a wide variety of tasks and input conditions. In particular, architectures such as recurrent neural networks, long short-term memory networks, and transformer-based models have demonstrated remarkable effectiveness in time-series forecasting scenarios, making them well-suited to the temporal structure of energy data.

The intelligent redirection component must operate reliably even in safety-critical conditions, where decisions carry significant real-world consequences and must therefore be auditable and formally verifiable. To address these requirements, the architecture incorporates a *symbolic reasoning* layer built upon techniques drawn from knowledge representation and formal methods. In particular, description logics, rule-based systems, ontology-driven reasoning, and formal verification techniques are employed to validate the consistency of system states and to enforce domain-specific constraints on energy redistribution decisions. These symbolic approaches offer a high degree of transparency and produce reasoning traces that can be systematically inspected and audited, properties that are essential in any application where accountability and safety are paramount.

By combining the complementary strengths of its neural and symbolic components, the proposed model embodies the *neurosymbolic* paradigm. Neural components excel at extracting rich representations from raw, high-dimensional data, while symbolic components enforce logical constraints and enable explicit reasoning. Their integration yields a system that is simultaneously accurate, adaptable and formally grounded. This design pattern aligns with an increasingly active and prominent research direction in artificial intelligence, motivated by the growing demand for *trustworthy AI* in critical domains. In contexts where the consequences of erroneous decisions can be severe, it is no longer sufficient for a system to be merely performant, it must also be verifiable and robust. The proposed architecture is conceived precisely with these requirements in mind, upholding the highest standards of quality assurance and operational safety.

3. Dataset and Prediction

Coherently with the neuro-symbolic nature of *GameL*, the dataset intended to feed the platform could be designed to serve a twofold purpose. On one hand, it should provide the temporal regularities and exogenous signals that the neural component may exploit to forecast short-term quantities; on the other hand, it should expose, at every time step, a synchronous snapshot of the energy community that could be lifted to the directed graph on which the symbolic layer would perform its strategic reasoning. For this reason, the dataset might be conceived not as a flat time series, but as a node-indexed multivariate time series sampled at hourly (or sub-hourly) granularity, so that each record would describe the state of a single entity within the community at a given instant.

More formally, one may consider a collection of tuples of the form: $\langle t, v, \tau(v), \mathbf{x}_v(t)\rangle$ where t denotes the timestamp, v represents a node of the community graph, $\tau(v)$ indicates its type (e.g., *prosumer*, *critical consumer*, *producer*), and $\mathbf{x}_v(t)$ is the vector of measurements associated with v at time t. Under this assumption, the set of all tuples sharing the same timestamp t would reconstruct the full state of the community at that instant and could constitute the input on which the symbolic layer instantiates the graph and reasons about admissible reconfigurations. The features populating each tuple $\mathbf{x}_v(t)$ could be organized into three groups, each potentially playing a distinct role in the predictive pipeline:

- **Physical Measurements:** Per-node data such as local renewable generation (`pv_gen_kwh`), electrical load (`load_kwh`), and, where applicable, the state of charge of storage devices (`battery_soc_pct`) or the operational status of controllable assets like heat pumps. These variables would describe the physical behavior of the device and could serve as the primary targets of the short-term forecasting task.
- **Environmental Context:** Shared regional metrics, most notably solar irradiance (`irradiance_wm2`) and ambient temperature (`temp_c`). Since these quantities are typically common to all nodes located in the same geographical zone, they could act as essential exogenous predictors for both generation and demand, helping the neural model disentangle device-specific behavior from weather-driven fluctuations.
- **Economic and Infrastructural Context:** Variables such as the hourly wholesale electricity price might provide the economic signal needed to reason about export, storage, and demand-shifting decisions. Additionally, a qualitative indicator of local grid congestion could represent operational conditions that might trigger the model response.

The predictive task assigned to the neural component could be considered central to the overall architecture of *GameL*. In this setting, the model might be trained to perform short-term forecasting over a horizon of k steps ahead, with k ranging from one hour up to one day, and could produce, for each node, a prediction of the expected generation, load, and, optionally, the wholesale price. Crucially, this forecasting task could be performed end-to-end on historical data, largely independently of the symbolic layer: the neural model would not need explicit awareness of the model or of the formulae that will later be evaluated on it. Such a separation of concerns would be intentional, as it would allow the neural component to be trained, updated, or replaced without necessarily altering the formal reasoning layer, while still providing it with predictive evidence to operate on near-future states of the community rather than solely on the current observed one.

4. System Modeling

The formal foundations of our approach provide a rigorous basis for reasoning about adaptive energy management in complex dynamic infrastructures. The logic-based framework described here is capable of representing the dynamic evolution of network structures, strategic decision making under constraints, and the trade-offs involved in maintaining critical services during failures.

As previously stated, it is possible to formally model an interconnected energetic community, meaning that every entity is capable of consume and produce energy in order to inject it in the grid in case of necessity. To model this behaviour we can consider each entity of the community as a node in a graph, which has different kinds of label (e.g. critical, prosumer, consumer etc...) and connected to each other via edges. Since we need to perform formal verification of properties expressed by a logic for strategic reasoning, this can be done using an extension of the well known Kripke Structure called Obstruction Model. Note that the classical formalization has a set of states S, which we replace by a set of nodes Q to make it more intuitive for our case. Let Ap be a finite set of atomic propositions. A *Kripke Structure* is a tuple $\langle Q, R, L\rangle$ where Q is a finite, non-empty set of nodes, $R \subseteq Q \times Q$ is a binary serial relation over Q (i.e., for any $q \in Q$ there exists an $q' \in Q$ such that $\langle q, q'\rangle \in R$), and $L : Q \to 2^{Ap}$ is a labeling function assigning a set of atomic propositions to any state $q \in Q$. An *obstruction model* M (or simply *model*) is given by $\langle Q, R, L, C\rangle$ where $\langle Q, R, L\rangle$ is a Kripke structure and $C : R \to \mathbb{N}^+$, with $\mathbb{N}^+$ being the positive natural numbers set, is a function assigning to any $\langle q, q'\rangle \in R$ a value $n \in \mathbb{N}^+$. According to this definition, a model is a finite directed graph in which nodes are labeled by a set of atomic propositions, describing the energetic state of the entity, and edges are labeled by positive integers, namely the quantity of energy passing from an entity to another. Consider the example illustrated in Figure 1; multiple substations supply energy to various nodes, including residential buildings and a central hospital. The hospital, as the most energy demanding and mission-critical node, depends on a stable and sufficient supply to ensure the continuity of essential medical services. If one of the substations were to experience a failure, the hospital could face a dangerous energy shortage, threatening patient safety and the reliability of the entire network. In such circumstances, the proposed system reacts adaptively by temporarily redistributing available electricity from less critical nodes, such as residential buildings, to support the hospital's immediate needs.

Figure 1: Comparison between a normal network and our framework's adaptive response. In (**i**), the network is working as expected. In (**ii**), a critical supply failure occurs, and our framework reallocates energy, reducing delivery to a household to keep the hospital fully powered.

To verify that the system can manage energy reallocation in safety-critical situations, such as the one described, we employ Obstruction Logic (OL) [10], a formal framework for strategic reasoning.

OL is designed to reason about dynamic systems represented as directed graphs, where connections, or edges, can be selectively deactivated to optimize the structure. In the energy management context, such a graph models an electrical network whose nodes correspond to control units, and whose connections represent power flows. OL captures dynamic modification eliminating arcs that are not useful or that obstruct the optimal operation of the system during the management of critical failure scenarios. At its core, OL combines principles from temporal and strategic logic to describe how the entities in the system can be managed over time following cuts to the network's structure. Its classical syntax extends traditional temporal logic with operators that express the existence of strategies capable of achieving or preventing certain states, considering a quantitative constraint (or grade) that limits how many or which edges can be deactivated. Semantically, OL interprets these strategies as functions defining which connections can be obstructed at each state, under given cost thresholds. Moreover, this structure allows one to rigorously verify whether an energy management system satisfies desired operational or safety properties under all possible reconfigurations. By expressing these properties as logical formulas, OL enables systematic checking that the network's control strategies comply with given constraints and optimization goals. This ensures that the process of eliminating non-useful arcs does not compromise stability, reliability, or efficiency, providing a formally verified guarantee of correct behavior across the entire electrical network.

However, the OL edge deactivation is only one aspect of the reconfiguration process. Once a set of connections has been obstructed, the energy that was flowing through those arcs must be redistributed across the remaining network in a way that is physically feasible and operationally sound. To address this, our framework incorporates a *flow replanning* component that operates downstream of the OL verification step, taking the reduced graph as input and computing a new feasible flow assignment over its active arcs. The flow replanning problem is defined over the subset of arcs that remain active after OL has applied its obstruction strategy and consists in finding an assignment that satisfies the capacity constraints on each active connection, the flow conservation constraints at every intermediate node, and the demand constraints at the sink nodes corresponding to critical users, such as hospitals and essential residential buildings. When the demand of critical nodes cannot be fully met even on the residual graph, the replanning component applies a priority-based load shedding policy, consistent with the node typing information encoded in the dataset, so that the available supply is directed first toward the highest-priority consumers.

The interaction between OL and the flow replanning module is therefore sequential and bidirectional. OL determines *which* arcs are to be obstructed, guided by the coalitional strategies verified on the model and constrained by the grade bound of the logic. The flow replanning module then determines *how* the energy is redistributed on the resulting topology, ensuring that the guarantee produced by OL, namely, that a winning strategy for the coalition exists, is translated into a concrete and physically realizable dispatch plan. If the replanning step reveals that the residual network is infeasible under the current obstruction, this information is fed back to the OL layer, which is prompted to explore alternative obstruction strategies within the same grade budget. This feedback loop ensures that the formal verification and the operational planning remain tightly coupled, preventing the framework from producing strategies that are logically valid but physically unimplementable.

Taken together, OL and the flow replanning component provide complementary guarantees: the former certifies the existence of a correct reconfiguration strategy at the symbolic level, while the latter produces the actual energy dispatch that realizes it at the physical level. This two-layer architecture ensures that the framework is both formally rigorous and practically deployable in real energy community management scenarios.

5. Conclusion

This paper introduced *GameL*, an ongoing research project aimed at developing an intelligent decision-support platform for energy communities. The proposed framework focuses on the modelling layer of the platform and combines three main elements: a node-indexed multivariate dataset, a neuro-symbolic reasoning architecture, and a formal layer for strategic verification. The dataset provides a common representation for both short-term forecasting and symbolic reasoning. The neural component predicts generation, load, and market signals up to one day ahead, while the symbolic component maps these predictions onto an Obstruction Model. There, Obstruction Logic is used to verify whether non-essential energy-flow arcs can be selectively deactivated while preserving the supply of critical nodes. Once a valid obstruction strategy is found, a flow replanning module computes a feasible redistribution of energy over the remaining network. In this way, *GameL* connects forecasting, verification, and dispatch, supporting energy communities with adaptive, explainable, and resilient decisions.

Future Work. As an immediate first step, efforts will be directed towards the construction of the envisioned dataset, carried out in close collaboration with the project partners, whose domain expertise and access to real-world operational data will be instrumental in ensuring its quality and representativeness. Following this, the neural component of the proposed model will be developed through a systematic investigation of state-of-the-art architectures for time-series forecasting, evaluating candidates such as recurrent models, transformer-based approaches, and hybrid solutions. Concurrently, the symbolic reasoning and formal verification layer will be designed and developed using the VITAMIN tool [44], with particular attention given to the selection of suitable agents and reasoning components. These efforts will ultimately converge in the full integration of the neural and symbolic components into a cohesive neurosymbolic system, to be validated through comprehensive experimentation on real-world energy management scenarios.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Gemini in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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