EI-TWIN: Energy Digital Twins for Renewable Energy Communities (Project Report)

Antonio Ielo, Francesco Ricca, Simone Ventrici and Michele Vitale

Università della Calabria

Abstract

We report on the EI-TWIN project, aimed at developing an AI-based platform for energy digital twins. The EI-TWIN platform relies on ASP for implementing some specific reasoning-based modules. The project targets two use cases: industrial energy efficiency in a pharmaceutical production facility, and optimization of Renewable Energy Communities (RECs). In this paper, we provide background on RECs, and as an example of activities carried out in the project, present an application of Answer Set Programming to the REC composition problem, i.e. selecting which members to include in a community as to maximize shared energy in the REC.

Keywords

Renewable Energy Communities, Answer Set Programming,

1. Introduction

The European Union has committed to reaching at least 42.5% renewable energy in its overall energy mix by 2030 [1]. This is driven by the need to reduce emissions, reduce external energy dependencies, and support industrial development strategy [2, 3]. Historically, Italy has met a large share of its overall energy demand through imports. This makes transitioning towards domestically produced renewable energy a national priority [4], especially in times of geopolitical tensions [5, 6, 7].

Unfortunately, deploying more renewable energy production infrastructure is not a sufficient nor viable solution to reach these goals. Power grids are designed for unidirectional flow from large centralized plants to passive consumers, while renewable energy sources are characterized by distributed and intermittent generation. Thus, renewable energy capacity growth poses several technical challenges in power grid management, such as increasing congestion and voltage instability [8, 9]. At the same time, increasing availability of smart metering, sensor networks, and cloud computing has created the preconditions for a data-driven approach to energy management [10, 11].

The EI-TWIN Project. Artificial Intelligence can play a central role in forecasting demand, optimizing asset dispatch, and coordinating distributed resources [12]. In this context, two complementary paradigms have emerged. On the one hand, the concept of an *Energy Digital Twin*—a virtual, continuously updated replica of a physical energy system, capable of predictive analysis and automated control through AI—offers a general-purpose tool for optimizing energy consumption at the level of individual buildings or industrial processes. On the other hand, the EU legislative framework on *Renewable Energy Communities* (RECs) has opened a new frontier: enabling groups of citizens, businesses, and local authorities to collectively produce, share, and benefit from renewable energy at the local level, with direct incentives tied to the amount of energy shared within the community.

This paper presents work carried out at the intersection of these two paradigms, within the **EI-TWIN** project (*Energy digital TWIN*), a 36-month research and innovation initiative funded under the Italian Ministry of Enterprises and Made in Italy's "Accordi per l'Innovazione" programme (D.M. 31/12/2021). The project brings together a consortium of four partners with complementary expertise:

CILC 2026: The 41st Italian Conference on Computational Logic, June 23–25, 2026, Ferrara, Italy
antonio.ielo@unical.it (A. Ielo); francesco.ricca@unical.it (F. Ricca); simone.ventrici@unical.it (S. Ventrici); michele.vitale@unical.it (M. Vitale)

- **Evogy**[1] (project lead), a green-tech company of the Plenitude/Eni group, specializing in IoT-based energy monitoring and AI-driven optimization of building energy assets;
- **Alens**[2], an independent energy consulting firm (certified ESCo), with extensive experience in energy audits, energy management, and monitoring across industrial and tertiary-sector buildings;
- **SALF**[3], a mid-sized pharmaceutical manufacturer whose energy-intensive production processes provide a concrete industrial testbed;
- **UNICAL**[4] (University of Calabria), contributing through the Artificial Intelligence research group of the Department of Mathematics and Computer Science (DEMACS), with expertise in machine learning, knowledge representation and reasoning, Answer Set Programming, and explainable AI.

The goal of EI-TWIN is the design and development of an AI-based platform for energy digital twins, validated on two complementary use cases that span different scales and domains of the energy landscape.

The first use case targets *industrial energy efficiency* within a pharmaceutical production facility. The manufacturing process involves multiple production lines with significant electricity and thermal consumption. The digital twin models the energy behavior of the plant's critical processes, enabling predictive analytics and automated control of HVAC systems and production scheduling to reduce energy waste while respecting operational and regulatory constraints.

The second use case—and the focus of this paper—targets *renewable energy communities* (RECs). Here, the digital twin models a community of buildings equipped with photovoltaic generation and battery storage, with the objective of maximizing shared energy (i.e., the portion of locally produced energy that is simultaneously consumed within the community) and minimizing exchanges with the national grid. The platform monitors consumption and production profiles across community members, and leverages AI techniques to optimize the dispatch of flexible assets (storage, controllable loads) in real time.

Role of UNICAL. Within the consortium, UNICAL is responsible for the research and development of the AI components of EI-TWIN. This includes both the training of machine learning components, the development of knowledge representation and reasoning modules based on Answer Set Programming (ASP). Examples include development of predictive models for energy consumption/production forecasting, and optimization algorithms for shared energy maximization.

From the research perspective, a major theme within the project concerns the scalability of ASP over large datasets. It is well known traditional ASP systems suffer from the so-called *grounding bottleneck*, which limits their applicability when the input data grows into thousands of facts. To address this, UNICAL is investigating compilation-based solving techniques [13, 14], in which non-ground rules are compiled into ad-hoc propagators that bypass the grounding phase entirely, enabling efficient reasoning over the large volumes of energy data handled by the EI-TWIN platform. Other research directions being investigated are the design of ASP solving algorithms to run over Big Data platforms [15], and the investigation of explainability [16, 17] and compliance-checking techniques [18].

2. Renewable Energy Communities

Renewable Energy Communities (RECs) are non-profit legal entities, where a group of participants (citizens, businesses, local authorities) collectively produce and consume renewable energy within the same geographical area. The primary purpose of RECs is to provide environmental, economic and social benefits to members and territory, rather than financial profits [19]. Participants may own generation

[1] https://www.evogy.it/
[2] https://www.alens.it/
[3] https://www.salfspa.it/
[4] https://www.unical.it/

assets ("producers"), only consume ("consumers"), or both ("prosumers"). RECs achieve their purpose by promoting *sharing renewable energy* between its members. Different states interpret the notion of "shared energy" differently [20, 21, 22]. In the Italian regulation, shared energy is defined as the minimum between the total renewable energy fed into the power grid by the members, and the total energy withdrawn by its consumers [23]. Intuitively, this is energy that is both produced and consumed locally, and impacts the power grid only at a local level.

Sharing energy tackles structural issues in the power grid. Grid congestion (i.e., electricity demand or distributed renewable generation exceeds available transmission capacity) is one of the biggest bottlenecks in Europe's energy transition [4, 8, 9].

The root cause is a collision between the rapid growth of distributed generation and electrification of transport and heating on one side, and aging infrastructure designed for unidirectional power flow from centralized plants on the other [9, 8]. By promoting local self-consumption, RECs reduce the volume of energy flowing through transmission and distribution infrastructure, alleviating congestion without requiring massive infrastructure upgrades. They also reduce transmission losses by shortening the distance between generation and consumption, and smooth load profiles, reducing stress on distribution network.

Optimizing shared energy From an optimization perspective, maximizing shared energy within a given community requires integrating multiple techniques, including optimization and machine learning [24, 25]. A classic approach, which we also applied in EI-TWIN, is *model predictive control* (MPC) [26]. In MPC, one learns the dynamics of controllable assets (in our usecase, HVACs and CO_2 fans) from data and computes an optimal actuation sequence via linear programming over a finite horizon, so as to shift the community's consumption profile to better overlap with local production while maintaining comfort bounds [27]. The effective deployment of this approach in RECs faces some practical issues. Members may be unwilling, due to domain constraints, to actuate certain actions; models may be inaccurate due to limited data availability; and, most critically, the controllable share of total consumption may simply be too small to affect the shared energy metric meaningfully. Moreover, at the time of writing, REC adoption in Italy is modest [28], which makes appropriate real-world scenarios where this approach is feasible hard to come by.

Composing RECs These factors motivate the focus on appropriately *composing* the community itself. Rather than shifting consumption profiles in real time—which may have only a marginal effect—one can select which producers and consumers to group together on the basis of their average historical consumption and production profiles [29, 30]. Indeed, complementary behaviors (i.e., pairing producers whose generation peaks coincide with the consumption peaks of selected consumers). In the next section, we discuss this problem.

3. An Example Application: Optimizing RECs Composition

We propose the use of Answer Set Programming to support the composition of RECs. Answer Set Programming (ASP; [31]) is a declarative programming paradigm based on the stable model semantics of logic programs [32]. Availability of efficient systems makes it a popular choice for addressing combinatorial and knowledge representation and reasoning problems in academic [33, 34] and industrial settings [35].

Let $U = \{u_1, \ldots, u_n\}$ be a set of prosumers, with each one of them being characterized by an average energy consumption and production behavior. We denote by $p_{i,t} \in \mathbb{R}^+$ and $c_{i,t} \in \mathbb{R}^+$ the production and consumption of u_i at time t. The *self-consumption* of u_i at time t is equal to $s_{i,t} = min(p_{i,t}, c_{i,t})$. Intuitively, the self-consumption is the share of energy that is produced by u_i that is also consumed, locally, by u_i itself, and is not transferred over the network. Conversely, the *injection* and *withdrawal* are the quantities $p_{i,t} - s_{i,t}$ and $c_{i,t} - s_{i,t}$, i.e. the share of energy that is put into the grid and withdrawn from the grid.

Given a set $S \subset U$, we define its *total injection* and *total withdrawal* at time t respectively as:

$$I(S,t) = \sum_{u_i \in S} p_{i,t} - s_{i,t} \qquad W(S,t) = \sum_{u_i \in S} c_{i,t} - s_{i,t}$$

We define the *shared energy* at time t as the quantity $Shared(S,t) = min(I(S,t), W(S,t))$, and the total shared energy as $Shared(S) = \sum_t Shared(S,t)$. We are interested in selecting S^* ("composing a CER") such that $Shared(S^*)$ is maximized. The problem can be straightforwardly modeled in ASP, in the classic guess, define and check fashion. In the rest of the section, we use the input language of the `clingo` [36] system.

Inputs. We assume input facts of the form $injection(m,t,v)$ and $withdrawal(m,t,v)$ to denote that the m-th prosumer withdraws (consumes) or injects (produces) respectively v units of energy at time-step t. For this application, we assume consumption and production are already *net*, that is self-consumption component has been removed both from production and consumption, yielding the net power withdrawal and injection in the grid. These may encode the *average behavior* of a prosumer (i.e., average weekly behavior), or the real consumption patterns over a time-window. As customary in ASP, real-valued inputs are mapped to integers assuming fixed-precision arithmetic.

We use the atom $member(p)$ to denote that p is a unique identifier for a prosumer, and $time(t)$ marks valid (discrete) steps in the input timeseries:

```
member(P) :- injection(P,_,_).
member(P) :- withdrawal(P,_,_).
time(T) :- injection(_,T,_).
time(T) :- withdrawal(_,T,_).
```

Selecting a REC. We use a choice rule to guess a subset of the input members, with `min_members` and `max_members` being `clingo` run-time constants that denote respectively the minimum size and maximum size of the community:

```
#const min_members.
#const max_members.
min_members { selected(P): member(P) } max_members.
```

Computing shared energy. We use the `#sum` aggregate to compute shared energy, as the point-wise minimum between total injection and withdrawal from the network:

```
total_injection(T,I) :- time(T), I=#sum{V,M: injection(M,T,V), selected(M)}.
total_withdrawal(T,W) :- time(T), W=#sum{V,M: withdrawal(M,T,V), selected(M)}.
shared(T,S) :- total_injection(T,I), total_withdrawal(T,W), S=#min{I;W}.
```

Finally, we optimise for the member selection that yields the most (cumulative) shared energy. As a tie-breaker, we also maximize the least shared energy.

```
:~ shared(T,E). [-E@2,T]
min_shared(W) :- W=#min{Z: shared(_,Z)}.
:~ min_shared(W). [-W@1]
```

Thus, optimal answer sets of the logic program represent subsets that yield the optimal (maximum) shared energy. As a proof of concept, we apply our encoding to the simulated environment shown in Figure 1. This includes $n = 8$ synthetically-generated production-consumption profiles. Figure 2 shows the cumulative shared energy of 100 random communities (of size at least 3), with the optimal CER computed with the ASP solver (bold).

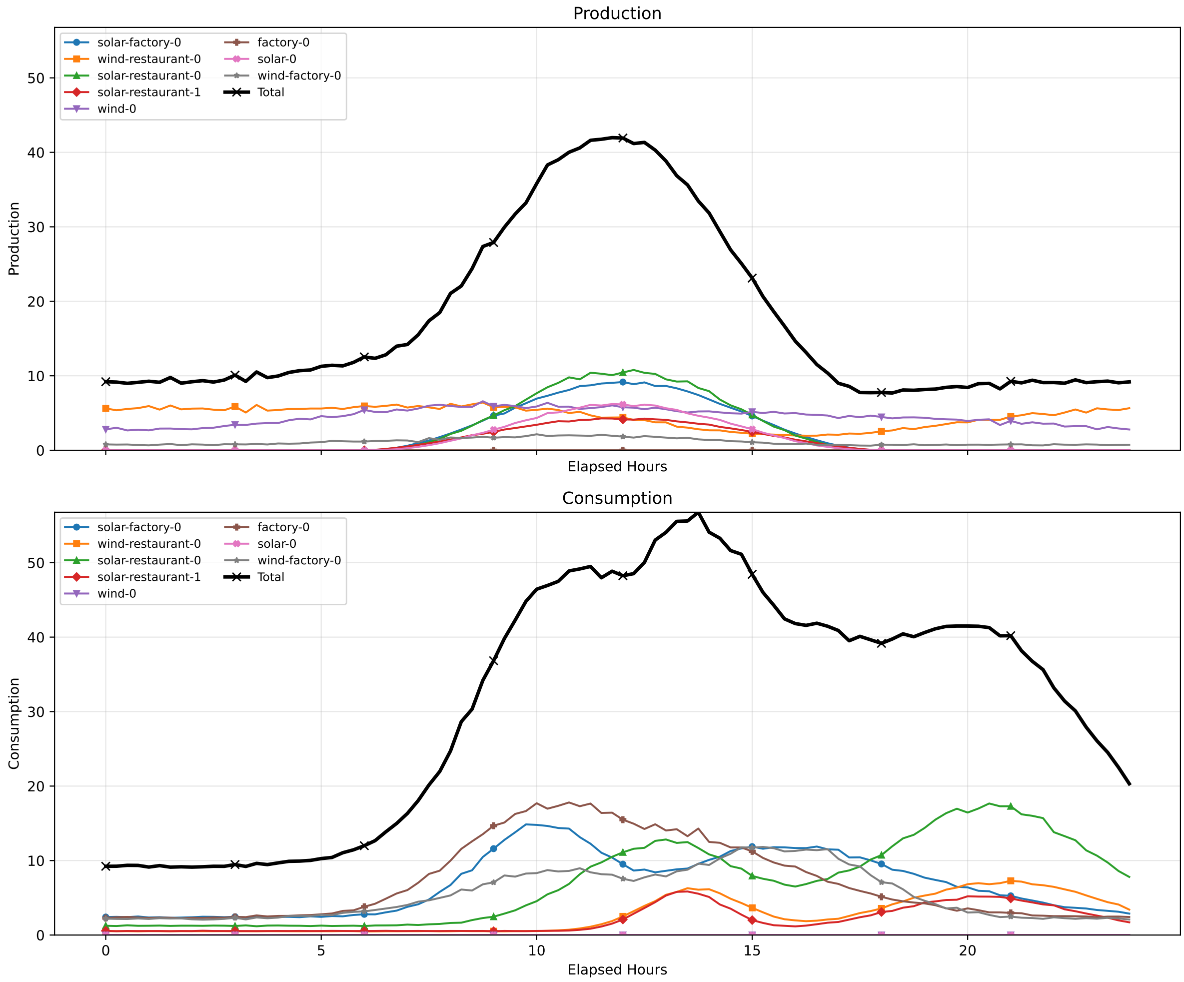

Figure 1: A synthetic scenario with 8 members, characterized by a production pattern (top) and a consumption pattern (bottom), over a 24 hours horizon.

3.1. Extensions

One advantage of a declarative solution for this problem is that it can be extended and customized to requirements' variants. On top of this base encoding, we can layer several extensions that help the development of support tools for REC composition, which have been or will be considered during the EI-TWIN project.

What-if analysis on community membership. Solving under the assumption (or, adding as facts) of some $include(m)$ atoms enables to understand what would be the best member to *add* to an existing REC, or what would be the impact on shared energy metrics of including a particular member. This can be useful for energy community managers to perform *what-if* analyses. Similarly, slight changes to the encoding enable to *partition* a set of members into several energy communities.

Storage elements. The role of storage elements (such as batteries) is also being investigated. The effect of including a battery is to *shift* the consumption and production curves for a specific prosumer. Indeed, the idea is to *avoid waste* by releasing on the grid energy that can't be readily used by other prosumers, charging a battery that will *later* release on the grid with discharge actions. Here, we plan to use ASP to "optimally control" the charge-discharge events of a battery, to provide an upper bound on the effect installing the battery would have on the shared energy of the community. We plan to do this by modeling batteries (over a fixed community) as a fictitious member, with charge and discharge

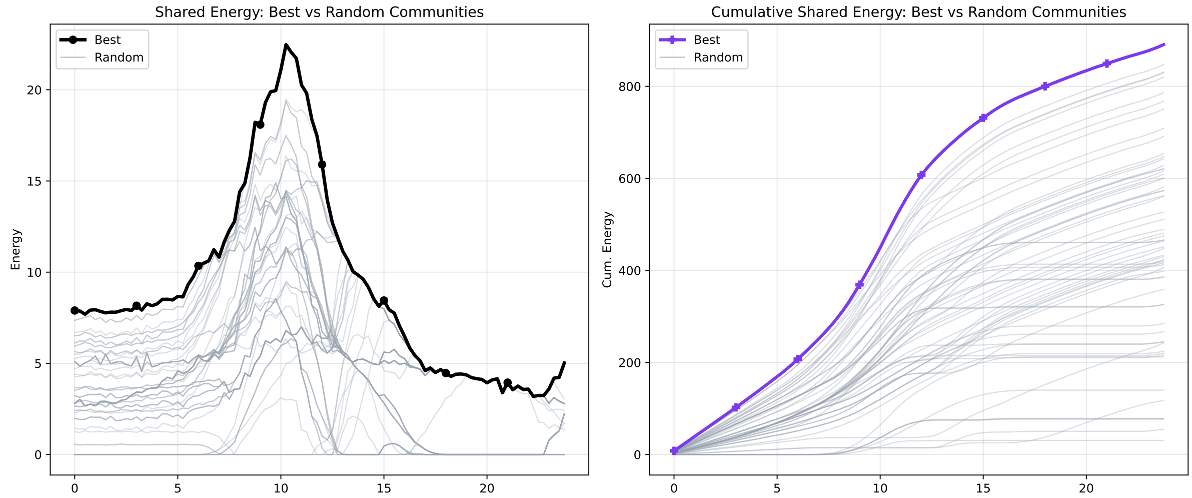

Figure 2: Shared energy (left) and cumulative shared energy (right) as a function of time, for different communities of size at least 3. Each line represents a community obtained as a random sample, out of 100 random samples. The bold line represents the community obtained by ASP optimization, which achieves the highest cumulative shared energy.

actions mapping to consumption and production.

Economic incentives. Whenever additional data about energy price or regulatory-specific economic incentives is available, additional optimization criteria may be added to the logic program. As an example, one might be interested in minimizing the impact of non-shared energy, i.e., the cost of withdrawn energy minus sold energy. Although this is not *the primary* aim of RECs, this has a direct impact on its members. Lexicographic multi-objective optimization criteria can be easily expressed by means of weak constraints, while more complex preferences can be expressed using `asprin` [37].

4. Conclusion

We presented a report on the EI-TWIN project, a research and innovation initiative aimed at developing an AI-based platform for energy digital twins. Within the consortium, the University of Calabria is responsible for the AI components of the platform, spanning machine learning models for energy forecasting and knowledge representation and reasoning modules based on Answer Set Programming. As an example of the activities carried out in the project, we presented an ASP-based approach to the REC composition problem, where the goal is to select community members so as to maximize shared energy. Current and future work includes the investigation of compilation-based ASP solving techniques to address the grounding bottleneck over the large-scale energy datasets handled by the platform.

Acknowledgements

This work was partially supported by the Italian Ministry of Industrial Development (MISE) under project EI-TWIN n. F/310168/05/X56 CUP B29J24000680005.

Declaration on Generative AI

Authors used LLMs for grammar checking and rephrasing. Authors edited and reviewed the content as needed, and take full responsibility for the publication's content.

References

[1] W. Lehnert, Y. Traum, The 'new'renewable energy directive (red iii): an overview, European Energy & Climate Journal 12 (2024) 40–47.

[2] A. C. Goldthau, R. Youngs, The eu energy crisis and a new geopolitics of climate transition, JCMS: Journal of Common Market Studies 61 (2023) 115–124. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jcms.13539. doi:https://doi.org/10.1111/jcms.13539. arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcms.13539.

[3] N. Scarlat, J.-F. Dallemand, F. Monforti-Ferrario, M. Banja, V. Motola, Renewable energy policy framework and bioenergy contribution in the european union – an overview from national renewable energy action plans and progress reports, Renewable and Sustainable Energy Reviews 51 (2015) 969–985. URL: https://www.sciencedirect.com/science/article/pii/S1364032115006346. doi:https://doi.org/10.1016/j.rser.2015.06.062.

[4] International Energy Agency, Italy 2023: Energy policy review, 2023. URL: https://www.iea.org/reports/italy-2023. doi:10.1787/278dd18f-en.

[5] J. Osička, F. Černoch, European energy politics after ukraine: The road ahead, Energy Research & Social Science 91 (2022) 102757. URL: https://www.sciencedirect.com/science/article/pii/S2214629622002602. doi:https://doi.org/10.1016/j.erss.2022.102757.

[6] M. Skalamera, The geopolitics of energy after the invasion of ukraine, The Washington Quarterly 46 (2023) 7–24. doi:10.1080/0163660X.2023.2190632.

[7] U. Keliauskaitė, B. McWilliams, T. Mramor, A. Roth, S. Tagliapietra, G. B. Wolff, How will the Iran conflict hit European energy markets?, 2026. URL: https://www.bruegel.org/first-glance/how-will-iran-conflict-hit-european-energy-markets.

[8] N. Mlilo, J. Brown, T. Ahfock, Impact of intermittent renewable energy generation penetration on the power system networks–a review, Technology and Economics of Smart Grids and Sustainable Energy 6 (2021) 25.

[9] E. Ejuh Che, K. Roland Abeng, C. D. Iweh, G. J. Tsekouras, A. Fopah-Lele, The impact of integrating variable renewable energy sources into grid-connected power systems: Challenges, mitigation strategies, and prospects, Energies 18 (2025). URL: https://www.mdpi.com/1996-1073/18/3/689.

[10] S. Aslam, P. P. Aung, A. S. Rafsanjani, A. P. A. Majeed, Machine learning applications in energy systems: current trends, challenges, and research directions, Energy Informatics 8 (2025) 62.

[11] Z. Chen, A. M. Amani, X. Yu, M. Jalili, Control and optimisation of power grids using smart meter data: A review, Sensors 23 (2023). URL: https://www.mdpi.com/1424-8220/23/4/2118.

[12] B. O. Abisoye, Y. Sun, W. Zenghui, A survey of artificial intelligence methods for renewable energy forecasting: Methodologies and insights, Renewable Energy Focus 48 (2024) 100529. URL: https://www.sciencedirect.com/science/article/pii/S1755008423001254. doi:https://doi.org/10.1016/j.ref.2023.100529.

[13] G. Mazzotta, F. Ricca, C. Dodaro, Compilation of aggregates in ASP systems, in: AAAI, AAAI Press, 2022, pp. 5834–5841.

[14] C. Dodaro, G. Mazzotta, F. Ricca, Compilation of tight ASP programs, in: ECAI, Frontiers in Artificial Intelligence and Applications, IOS Press, 2023, pp. 557–564.

[15] A. Cuteri, G. Mazzotta, F. Ricca, Toward executing datalog on big data platforms, in: CILC, CEUR Workshop Proceedings, CEUR-WS.org, 2025.

[16] I. Huitzil, G. Mazzotta, R. Peñaloza, F. Ricca, Asp-based axiom pinpointing for description logics, in: Description Logics, CEUR Workshop Proceedings, CEUR-WS.org, 2023.

[17] A. Ielo, G. Mazzotta, F. Ricca, R. Peñaloza, Towards asp-based minimal unsatisfiable cores enumeration for ltlf, in: OVERLAY, CEUR Workshop Proceedings, CEUR-WS.org, 2024, pp. 49–55.

[18] V. Barbara, M. Guarascio, N. Leone, G. Manco, A. Quarta, F. Ricca, E. Ritacco, Neuro-symbolic AI for compliance checking of electrical control panels, Theory Pract. Log. Program. 23 (2023) 748–764.

[19] European Parliament and Council of the European Union, Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy

from renewable sources (recast), 2018. URL: https://eur-lex.europa.eu/eli/dir/2018/2001/oj, official Journal of the European Union, L 328, 21 December 2018, pp. 82–209.
[20] V. Z. Gjorgievski, B. Velkovski, F. D. Minuto, S. Cundeva, N. Markovska, Energy sharing in european renewable energy communities: Impact of regulated charges, Energy 281 (2023) 128333. URL: https://www.sciencedirect.com/science/article/pii/S0360544223017279. doi:https://doi.org/10.1016/j.energy.2023.128333.
[21] E. Tarpani, C. Piselli, C. Fabiani, I. Pigliautile, E. J. Kingma, B. Pioppi, A. L. Pisello, Energy communities implementation in the european union: Case studies from pioneer and laggard countries, Sustainability 14 (2022). URL: https://www.mdpi.com/2071-1050/14/19/12528.
[22] A. Caramizaru, A. Uihlein, et al., Energy communities: an overview of energy and social innovation, volume 30083, Publications Office of the European Union Luxembourg, 2020.
[23] ARERA, Deliberazione 727/2022/r/eel – Testo Integrato Autoconsumo Diffuso (TIAD), 2022. URL: https://www.arera.it/fileadmin/allegati/docs/22/727-22.pdf, allegato A alla Deliberazione 27 dicembre 2022.
[24] A. Cosic, M. Stadler, M. Mansoor, M. Zellinger, Mixed-integer linear programming based optimization strategies for renewable energy communities, Energy 237 (2021) 121559.
[25] M. Matos, J. Almeida, P. Gonçalves, F. Baldo, F. J. Braz, P. C. Bartolomeu, A machine learning-based electricity consumption forecast and management system for renewable energy communities, Energies 17 (2024) 630.
[26] K. S. Holkar, L. M. Waghmare, An overview of model predictive control, International Journal of control and automation 3 (2010) 47–63.
[27] G. Serale, M. Fiorentini, A. Capozzoli, D. Bernardini, A. Bemporad, Model predictive control (mpc) for enhancing building and hvac system energy efficiency: Problem formulation, applications and opportunities, Energies 11 (2018) 631.
[28] S. Brunoro, G. Bizzarri, E. Boldrin, Exploring the potential of energy communities in the italian territory, Frontiers in Built Environment Volume 10 - 2024 (2024). URL: https://www.frontiersin.org/journals/built-environment/articles/10.3389/fbuil.2024.1365115. doi:10.3389/fbuil.2024.1365115.
[29] E. Schito, L. Taverni, P. Conti, D. Testi, Optimization of the composition of residential buildings in a renewable energy community based on monitored data, Optimization and Engineering 26 (2025) 733–751.
[30] A. D. Mustika, R. Rigo-Mariani, V. Debusschere, A. Pachurka, New members selection for the expansion of energy communities, Sustainability 14 (2022). URL: https://www.mdpi.com/2071-1050/14/18/11257.
[31] G. Brewka, T. Eiter, M. Truszczynski, Answer set programming at a glance, Commun. ACM 54 (2011) 92–103.
[32] M. Gelfond, V. Lifschitz, The stable model semantics for logic programming, in: ICLP/SLP, MIT Press, 1988, pp. 1070–1080.
[33] E. Erdem, V. Patoglu, Applications of ASP in robotics, Künstliche Intell. 32 (2018) 143–149.
[34] E. Erdem, M. Gelfond, N. Leone, Applications of answer set programming, AI Mag. 37 (2016) 53–68.
[35] A. A. Falkner, G. Friedrich, K. Schekotihin, R. Taupe, E. C. Teppan, Industrial applications of answer set programming, Künstliche Intell. 32 (2018) 165–176.
[36] M. Gebser, R. Kaminski, B. Kaufmann, T. Schaub, Multi-shot ASP solving with clingo, Theory Pract. Log. Program. 19 (2019) 27–82.
[37] G. Brewka, J. P. Delgrande, J. Romero, T. Schaub, A general framework for preferences in answer set programming, Artif. Intell. 325 (2023) 104023.