# FEDERATED MULTI-AGENT INTELLIGENCE FOR SMART RENEWABLE ENERGY ECOSYSTEMS

**Adina-Georgeta CREȚAN***

**Abstract**

*The rapid evolution of renewable energy technologies and decentralized power infrastructures has transformed the way modern energy ecosystems operate. Renewable Energy Communities (RECs) are increasingly adopting intelligent digital solutions to improve sustainability, operational flexibility, and resource optimization. However, the heterogeneous nature of distributed renewable resources — including photovoltaic systems, wind turbines, battery storage units, and electric vehicle charging stations — introduces significant challenges regarding interoperability, coordination, and autonomous decision-making in dynamic environments.*

*This paper proposes an AI-driven collaborative framework designed to support adaptive coordination and distributed decision-making among autonomous renewable energy entities operating inside smart energy communities. The proposed approach integrates advanced technologies such as Multi-Agent Systems (MAS), Federated Learning, Edge AI, Digital Twin models, and Explainable Artificial Intelligence (XAI) to facilitate real-time cooperation while preserving the autonomy and privacy of each participant.*

*Within the proposed architecture, intelligent software agents continuously analyze energy demand, renewable production capacity, storage availability, and network constraints in order to dynamically negotiate energy redistribution and resource allocation strategies. Unlike centralized coordination approaches, the framework enables decentralized collaboration through adaptive communication services and intelligent negotiation mechanisms capable of synchronizing multiple simultaneous interactions between distributed energy participants.*

*To improve resilience and operational efficiency, the system also incorporates predictive analytics and machine learning algorithms that support demand forecasting, anomaly detection, and adaptive energy balancing. In addition, Digital Twin technology is employed to simulate and optimize the behavior of renewable energy infrastructures under varying environmental and operational conditions.*

*The proposed framework contributes to the development of sustainable and interoperable smart energy ecosystems by enhancing flexibility, reducing coordination latency, and supporting intelligent cooperation among distributed renewable energy communities.*

**Keywords***: Renewable Energy Communities, Artificial Intelligence, Multi-Agent Systems, Federated Learning, Digital Twin, Edge AI, Explainable AI, Smart Energy Systems, Distributed Renewable Resources.*

## 1. Introduction

The global transition toward sustainable energy infrastructures has accelerated the development of decentralized renewable energy systems capable of operating autonomously and intelligently inside highly dynamic environments. Increasing energy consumption, climate change concerns, carbon reduction policies, and the growing integration of renewable energy resources have transformed traditional power networks into complex digital ecosystems that require advanced coordination and adaptive decision-making mechanisms.

In this context, Renewable Energy Communities (RECs) have emerged as an innovative paradigm for distributed energy management. A Renewable Energy Community represents a collaborative ecosystem composed of interconnected renewable energy entities such as photovoltaic installations, wind turbines, battery storage systems, smart buildings, and electric vehicle charging stations. These entities cooperate in order to optimize energy production, consumption, storage, and distribution while maintaining operational autonomy and reducing dependency on centralized power infrastructures.

Although decentralized renewable systems provide important advantages regarding sustainability and energy resilience, they also introduce major technical challenges. Renewable energy production is highly

* Associate Professor, PhD, Faculty of Economics and Business Administration, Computer Science Department, „Nicolae Titulescu" University of Bucharest (e-mail: adina.cretan@univnt.ro).

dependent on environmental conditions and may fluctuate significantly over short periods of time. Solar panels depend on weather conditions and sunlight availability, while wind turbines are influenced by wind intensity variations. Consequently, distributed renewable infrastructures require intelligent coordination services capable of dynamically balancing production, consumption, and storage activities in real time.

Recent advances in Artificial Intelligence (AI) and distributed computing technologies provide promising solutions for addressing these challenges. AI technologies enable autonomous systems to analyze large volumes of data, identify patterns, predict future events, and automatically optimize operational decisions without continuous human intervention. In the context of renewable energy ecosystems, AI can support demand forecasting, energy optimization, adaptive scheduling, anomaly detection, and distributed resource coordination.

One of the most important technologies integrated into modern intelligent energy systems is represented by Multi-Agent Systems (MAS). A Multi-Agent System consists of several autonomous software agents capable of interacting, collaborating, negotiating, and making independent decisions inside distributed environments. Each intelligent agent can represent a renewable energy entity, such as a solar station, a wind farm, or a battery storage unit. These agents continuously exchange information regarding energy production capacity, local consumption, operational constraints, and resource availability in order to coordinate collaborative activities. Within the proposed framework, MAS technology is used to support decentralized decision-making and adaptive negotiation among renewable energy participants.

Another important technology addressed in this research is Federated Learning (FL). Federated Learning is a distributed machine learning approach where multiple entities collaboratively train AI models without transferring sensitive local data to a central server. Instead of sharing raw information, participants exchange only model parameters or learning updates. This technology is particularly important in renewable energy communities because it preserves data privacy and reduces security risks while still enabling collaborative optimization. In the proposed framework, Federated Learning allows distributed renewable entities to improve forecasting and optimization models without exposing confidential operational information.

The paper also integrates Edge AI technology to improve real-time responsiveness inside distributed energy infrastructures. Edge AI refers to the execution of artificial intelligence algorithms directly at the edge of the network, close to data sources and physical devices, instead of relying exclusively on centralized cloud infrastructures. Through Edge AI, renewable energy entities can perform local data processing, rapid decision-making, and immediate anomaly detection with minimal communication latency. This capability becomes essential in environments where operational decisions must be taken quickly to prevent instability or energy imbalance.

In addition, the proposed architecture incorporates Digital Twin technology. A Digital Twin is a virtual representation of a physical system capable of continuously simulating, monitoring, and analyzing its real-world behavior using real-time operational data. In renewable energy systems, Digital Twins can reproduce the operational status of solar panels, wind turbines, storage systems, or entire energy communities. The Digital Twin models integrated into this work are used to simulate energy flows, evaluate operational scenarios, predict failures, and optimize coordination strategies before applying them in the real infrastructure.

Another relevant technology considered in this paper is Explainable Artificial Intelligence (XAI). Traditional AI models often behave as "black boxes," generating decisions without providing understandable explanations regarding the reasoning process. XAI addresses this limitation by offering transparent and interpretable explanations for AI-generated decisions. In renewable energy ecosystems, explainability is extremely important because operators and decision-makers must understand why specific energy allocation, forecasting, or negotiation decisions are recommended. In the proposed framework, XAI mechanisms improve transparency, trust, and human supervision of intelligent coordination processes.

To support interoperability and scalable communication between heterogeneous renewable entities, the proposed system also relies on cloud-based collaborative infrastructures and adaptive communication protocols. These technologies facilitate secure information exchange, synchronization of distributed activities, and coordination of multiple simultaneous interactions among autonomous participants.

The objective of this paper is to develop an intelligent collaborative framework capable of supporting adaptive coordination and distributed decision-making among autonomous renewable energy entities operating inside Renewable Energy Communities. The proposed approach combines Artificial Intelligence, Multi-Agent

Systems, Federated Learning, Edge AI, Digital Twin technology, and Explainable AI to improve interoperability, operational flexibility, sustainability, and resource optimization in decentralized smart energy ecosystems.

Unlike traditional centralized approaches, the proposed framework preserves participant autonomy while enabling intelligent collaboration through adaptive negotiation and distributed coordination mechanisms. The system is designed to facilitate dynamic energy redistribution, real-time resource management, and cooperative balancing strategies under continuously changing environmental and operational conditions.

The remainder of the paper is organized as follows. Section 2 presents the related work concerning AI-driven renewable energy management, intelligent coordination mechanisms, and distributed smart energy systems. Section 3 describes the proposed collaborative architecture and the associated intelligent coordination model. Section 4 details the adaptive negotiation and distributed decision-making mechanisms integrated into the framework. Finally, the last section presents the conclusions and future research directions.

## 2. Related work

The increasing complexity of decentralized renewable energy infrastructures has generated significant research interest in intelligent coordination mechanisms capable of supporting cooperation among autonomous renewable energy entities. Recent advances in Artificial Intelligence, distributed computing, and smart energy management have accelerated the development of adaptive frameworks designed to improve sustainability, interoperability, and operational efficiency inside Renewable Energy Communities (RECs).

One of the most widely investigated research directions concerns the integration of Artificial Intelligence techniques into distributed renewable energy management systems. AI-based approaches are increasingly used to optimize energy production, forecast renewable generation, detect anomalies, and improve adaptive decision-making processes. According to Ahmed and Park (2024), machine learning algorithms can significantly improve the accuracy of renewable energy forecasting by continuously analyzing historical production data, meteorological conditions, and consumption patterns. Their study demonstrates that AI-driven prediction models contribute to reducing energy imbalance and improving resource allocation efficiency inside decentralized smart grids.

Another important research area focuses on the use of Multi-Agent Systems (MAS) for distributed coordination and autonomous cooperation among renewable energy participants. Multi-agent architectures are considered particularly suitable for dynamic environments because autonomous agents can independently manage local objectives while simultaneously participating in collaborative activities. In the work proposed by Li and Wang (2023), intelligent software agents coordinate distributed renewable resources through adaptive negotiation mechanisms capable of dynamically adjusting energy exchange agreements according to changing operational conditions. Their research highlights the advantages of decentralized coordination compared with traditional centralized control approaches.

The concept of autonomous negotiation among distributed renewable entities has also attracted considerable attention in recent years. Wu and Huang (2024) propose a parallel negotiation framework where intelligent agents simultaneously negotiate energy redistribution and load-balancing strategies in interconnected renewable infrastructures. Their results indicate that adaptive negotiation mechanisms improve system flexibility and reduce coordination latency in highly dynamic energy environments.

Recent studies also investigate the integration of Federated Learning (FL) into smart renewable energy systems. Federated Learning enables multiple distributed entities to collaboratively train Artificial Intelligence models without transferring sensitive local information to centralized servers. This technology has become increasingly important because renewable energy infrastructures generate large volumes of operational data that may contain confidential or commercially sensitive information. Moreno et al. (2025) emphasize that Federated Learning improves privacy preservation and cybersecurity while still enabling collaborative optimization across distributed energy communities. Their research demonstrates that distributed learning approaches can significantly enhance forecasting accuracy and adaptive energy management.

Another promising direction concerns the application of Edge AI in renewable energy ecosystems. Edge AI allows intelligent data processing and decision-making to be performed directly near physical devices and sensors, reducing communication latency and dependence on centralized cloud infrastructures. Gupta and Sharma (2023) propose an Edge AI architecture for distributed renewable resource management capable of supporting real-time monitoring and adaptive coordination. Their approach improves responsiveness during rapid fluctuations in renewable energy production and enhances operational resilience in distributed environments.

Cloud computing technologies also play an essential role in supporting interoperability and scalable collaboration among autonomous renewable entities. Chen et al. (2024) introduce a cloud-assisted intelligent coordination platform integrating AI-based optimization services with distributed communication mechanisms. Their framework facilitates dynamic energy scheduling, adaptive resource sharing, and collaborative decision-making among heterogeneous renewable infrastructures. The study underlines the importance of flexible cloud-based services for managing large-scale renewable energy ecosystems.

In parallel, Digital Twin technology has become an important component of modern smart energy systems. A Digital Twin represents a virtual replica of a physical infrastructure capable of simulating operational behavior using real-time data collected from sensors and monitoring systems. According to Ferreira et al. (2025), Digital Twins improve predictive maintenance, operational optimization, and fault detection inside renewable energy communities. Their research demonstrates that simulation-driven coordination mechanisms allow distributed renewable infrastructures to anticipate operational risks and optimize energy balancing strategies before implementing real-world decisions.

Another important challenge addressed in recent literature concerns interoperability among heterogeneous renewable energy systems. Distributed infrastructures often include components developed using different technologies, communication protocols, and operational standards, making seamless collaboration difficult to achieve. Kumar et al. (2025) analyze interoperability challenges in decentralized smart energy systems and propose adaptive communication services capable of supporting flexible interactions among autonomous renewable entities. Their work highlights that interoperability is fundamental for enabling large-scale cooperation inside Renewable Energy Communities.

The emergence of Explainable Artificial Intelligence (XAI) has also influenced the development of intelligent renewable energy management systems. Traditional AI algorithms frequently operate as opaque “black-box” models that provide limited transparency regarding their decision-making processes. Santos and Ferreira (2023) argue that explainability is essential in smart energy ecosystems because operators must understand the reasoning behind AI-generated recommendations related to energy allocation, forecasting, or adaptive coordination. Their research demonstrates that XAI mechanisms increase user trust and facilitate human supervision of autonomous decision-making systems.

Despite the considerable progress achieved in these research areas, several limitations remain insufficiently addressed. Many existing approaches rely on centralized coordination models that reduce participant autonomy and increase dependency on centralized infrastructures. Other solutions focus only on isolated optimization mechanisms without considering simultaneous negotiations, adaptive interoperability, and distributed collaboration inside dynamic Renewable Energy Communities.

Compared with existing research contributions, the framework proposed in this paper integrates Artificial Intelligence, Multi-Agent Systems, Federated Learning, Edge AI, Digital Twin technology, Explainable AI, and adaptive negotiation services into a unified collaborative architecture dedicated to autonomous renewable energy ecosystems. The proposed approach emphasizes decentralized coordination, privacy preservation, interoperability, and intelligent cooperation among distributed renewable energy participants operating under continuously changing environmental and operational conditions.

### 2.1. Automated Negotiation in Renewable Energy Communities

The rapid expansion of decentralized renewable energy infrastructures has significantly increased the need for intelligent coordination mechanisms capable of supporting autonomous interactions among distributed energy participants. In Renewable Energy Communities (RECs), multiple independent entities continuously interact in order to balance energy production, storage, and consumption under highly dynamic operational conditions. Because renewable resources are inherently variable and distributed across heterogeneous infrastructures, efficient collaboration requires adaptive and automated negotiation mechanisms capable of supporting real-time decision-making.

Automated negotiation represents a distributed decision-making process in which autonomous entities exchange proposals, counterproposals, and coordination requests in order to reach mutually acceptable agreements without direct human intervention. In the context of renewable energy ecosystems, negotiation mechanisms can support various collaborative activities such as energy redistribution, dynamic load balancing, resource allocation, storage optimization, and cooperative scheduling.

Traditional centralized energy coordination approaches are often limited by scalability issues, communication bottlenecks, reduced flexibility, and the excessive exposure of sensitive operational information. As Renewable Energy Communities continue to expand, centralized architectures become increasingly difficult to maintain due to the large number of heterogeneous participants and continuously changing environmental conditions. Consequently, decentralized automated negotiation has emerged as a promising alternative for supporting intelligent cooperation among autonomous renewable energy entities.

Recent advances in Artificial Intelligence have significantly improved the capabilities of automated negotiation systems. AI-driven negotiation mechanisms enable autonomous entities to dynamically analyze operational constraints, evaluate alternative coordination strategies, predict future energy demands, and adapt negotiation behavior according to changing environmental conditions. Intelligent negotiation agents can continuously optimize their decisions based on historical interactions, renewable energy forecasts, and real-time network conditions.

Within modern renewable energy ecosystems, Multi-Agent Systems (MAS) are frequently employed to implement automated negotiation processes. Each intelligent software agent may represent a distributed renewable entity such as a photovoltaic station, a wind turbine cluster, a battery storage unit, or an electric vehicle charging infrastructure. These agents autonomously manage local objectives while participating in collaborative negotiations with other entities inside the energy community.

Negotiation processes in distributed renewable environments typically involve multiple interdependent attributes, including available energy capacity, storage level, response time, operational cost, energy demand, and environmental conditions. Consequently, negotiation mechanisms must support complex multi-attribute decision-making while maintaining system scalability and operational efficiency.

Federated Learning contributes to automated negotiation by enabling distributed renewable entities to collaboratively improve prediction and optimization models without exchanging confidential operational data. Through decentralized learning processes, intelligent agents can enhance negotiation strategies while preserving participant privacy and reducing cybersecurity risks. This capability is particularly important in energy ecosystems where operational information may contain commercially sensitive data.

Edge AI technologies further improve automated negotiation efficiency by enabling local processing and real-time decision-making directly at the edge of the network. Instead of transmitting all operational information to centralized cloud infrastructures, intelligent agents can locally evaluate negotiation conditions, detect anomalies, and rapidly respond to dynamic changes in renewable energy production and consumption. This reduces communication latency and increases system responsiveness during critical operational situations.

Digital Twin technology also plays an important role in intelligent negotiation environments. By maintaining virtual replicas of physical renewable infrastructures, Digital Twins allow autonomous agents to simulate negotiation outcomes, evaluate coordination scenarios, and predict operational risks before applying decisions in the real system. Simulation-driven negotiation improves system reliability and supports proactive resource management inside distributed energy communities.

Another critical aspect of automated negotiation concerns transparency and trustworthiness. In many traditional AI systems, decision-making processes are difficult to interpret due to the opaque nature of machine learning algorithms. Explainable Artificial Intelligence (XAI) addresses this limitation by providing interpretable explanations regarding negotiation decisions and resource allocation strategies. Through XAI mechanisms, renewable energy operators can better understand the reasoning behind AI-generated negotiation outcomes, increasing confidence in autonomous coordination systems.

Recent research efforts increasingly focus on adaptive and decentralized negotiation architectures capable of supporting simultaneous interactions among multiple autonomous renewable entities. These approaches aim to improve interoperability, operational resilience, energy efficiency, and sustainability while preserving the autonomy of participating entities.

Compared with conventional coordination models, automated negotiation offers several important advantages for Renewable Energy Communities, including:

- decentralized decision-making,
- adaptive resource allocation,

- reduced operational latency,
- scalability in dynamic environments,
- privacy preservation,
- improved interoperability,
- intelligent cooperation among heterogeneous renewable infrastructures.

In this context, automated negotiation becomes a fundamental component of next-generation smart renewable energy ecosystems, enabling autonomous renewable entities to collaboratively manage distributed resources in a flexible, intelligent, and sustainable manner.

## 3. Multi-Agent Coordination and Automated Negotiation

The increasing complexity of Renewable Energy Communities requires intelligent coordination mechanisms capable of supporting distributed decision-making and adaptive cooperation between autonomous renewable entities. Unlike traditional centralized energy systems, decentralized renewable infrastructures operate in highly dynamic environments where production capacity, energy demand, and operational constraints continuously evolve.

To address these challenges, the proposed framework integrates Multi-Agent Systems, Artificial Intelligence techniques, and adaptive negotiation mechanisms in order to facilitate real-time coordination between distributed renewable participants. Intelligent agents are capable of exchanging information, evaluating operational conditions, and dynamically negotiating resource allocation strategies while preserving the autonomy of each entity.

The proposed coordination model focuses on interoperability, flexibility, and scalability, enabling renewable energy entities to cooperate efficiently without relying on centralized control infrastructures. In this context, interaction management and automated negotiation become essential mechanisms for ensuring intelligent collaboration inside Renewable Energy Communities.

### 3.1. Interactions in Renewable Energy Communities

In Renewable Energy Communities, autonomous renewable entities continuously interact in order to coordinate energy production, storage, and consumption activities. These interactions may involve photovoltaic systems, wind farms, battery storage infrastructures, smart buildings, or electric vehicle charging stations operating inside distributed smart energy ecosystems.

The interaction process enables renewable entities to exchange operational information, negotiate energy redistribution, coordinate flexibility services, and dynamically adapt to changing environmental conditions. Intelligent software agents facilitate these interactions through distributed communication mechanisms capable of supporting autonomous cooperation and adaptive decision-making.

Within the proposed framework, communication between agents is based on structured conversations and negotiation protocols. Agents may exchange requests, proposals, counterproposals, and coordination messages while preserving local autonomy and limiting unnecessary information disclosure.

Because renewable environments are highly dynamic, interactions must support real-time adaptation, distributed reasoning, and interoperability between heterogeneous infrastructures. In this context, Artificial Intelligence technologies such as Multi-Agent Systems, Edge AI, and Federated Learning improve the capability of renewable entities to cooperate efficiently under fluctuating operational conditions.

### 3.2. Coordination of Interactions

Coordination represents an essential mechanism for maintaining coherent collaboration between autonomous renewable entities. In distributed renewable energy systems, multiple agents may simultaneously participate in different negotiations while managing local operational objectives and constraints.

The proposed framework combines distributed coordination and adaptive negotiation mechanisms in order to support efficient cooperation without centralized control. Coordination services supervise communication consistency, synchronization between simultaneous negotiations, and adaptive resource allocation across the Renewable Energy Community.

Two coordination approaches are considered within the proposed architecture:

- generic coordination, focused on communication and interoperability services;
- strategic coordination, focused on intelligent decision-making and adaptive negotiation strategies.

The coordination process may also be:

- local, when agents manage their own negotiations independently;
- global, when shared protocols and coordination rules are applied to all participants in the system.

Unlike centralized energy management architectures, the proposed distributed coordination approach preserves participant autonomy while improving scalability, flexibility, and resilience inside dynamic renewable energy ecosystems.

### 3.3. Multi-Agent Automated Negotiation Mechanism

Automated negotiation enables autonomous renewable entities to collaboratively manage distributed resources without direct human intervention. Intelligent agents exchange proposals and counterproposals in order to establish agreements regarding energy redistribution, storage allocation, delivery intervals, or operational flexibility.

The negotiation process evolves through three main stages:

- partner identification,
- negotiation refinement,
- agreement establishment.

During negotiation, agents evaluate multiple operational attributes such as energy quantity, storage availability, operational cost, response time, and renewable production forecasts. Because these attributes are often interdependent, negotiation strategies must support adaptive multi-attribute reasoning.

The negotiation protocol defines the communication rules governing the interaction between agents, while the negotiation strategy determines how agents generate and evaluate proposals according to local objectives and environmental conditions.

Artificial Intelligence technologies significantly improve negotiation efficiency. Federated Learning enables collaborative optimization without exposing confidential data, Edge AI supports real-time local decision-making, while Digital Twin models allow renewable entities to simulate operational scenarios before applying negotiated decisions in the physical infrastructure.

Through these mechanisms, automated negotiation becomes a key component for enabling intelligent cooperation, interoperability, and adaptive resource management inside Renewable Energy Communities.

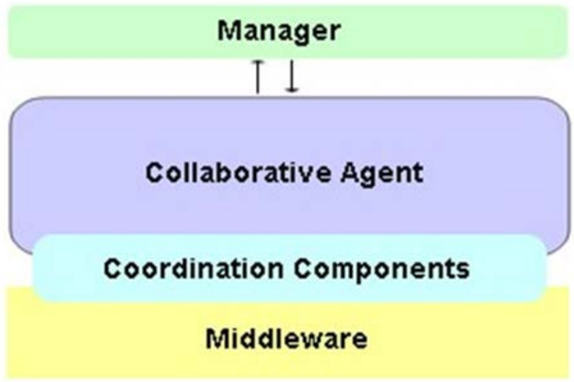
## 4. Collaborative Renewable Energy Architecture

The primary objective of the proposed software infrastructure is to support collaborative activities inside Renewable Energy Communities composed of autonomous and geographically distributed renewable energy entities. These entities may include photovoltaic systems, wind energy infrastructures, battery storage units, smart buildings, electric vehicle charging stations, or distributed renewable resource providers operating within the same smart energy ecosystem.

Because each renewable entity preserves its operational autonomy and manages its own local objectives, direct centralized control becomes difficult to implement efficiently. Consequently, intelligent negotiation and distributed coordination mechanisms become essential for enabling secure and adaptive cooperation between independent participants.

Figure 1 illustrates the proposed collaborative renewable energy architecture.

**Figure 1. The architecture of the collaborative renewable energy system**




The proposed architecture is structured into four main layers: Manager Layer, Intelligent Collaborative Agent Layer, Coordination Components Layer, and Middleware Layer.

The Manager Layer supervises the operational activities of each renewable energy participant and defines local objectives, constraints, priorities, and energy policies. The manager may represent either a human operator or an autonomous management service responsible for controlling local renewable resources.

The Intelligent Collaborative Agent Layer assists the manager by coordinating local and global interactions with other renewable entities. At the local level, the agent manages negotiations associated with a specific energy request or operational task. At the global level, the agent supervises multiple simultaneous negotiations involving several distributed participants. Intelligent agents continuously evaluate operational parameters such as renewable production forecasts, storage availability, energy demand, network conditions, and environmental constraints.

The Coordination Components Layer manages dependencies and synchronization constraints between multiple negotiations occurring simultaneously within the Renewable Energy Community. This layer enables distributed coordination between renewable entities while preserving participant autonomy and limiting unnecessary information exchange.

The Middleware Layer ensures communication interoperability between heterogeneous renewable infrastructures and supports message exchange between distributed intelligent agents. The middleware also facilitates adaptive communication services, synchronization mechanisms, and secure information transfer across the renewable ecosystem.

Within the proposed framework, each negotiation evolves through three main phases: initialization, refinement, and agreement establishment.

During the initialization phase, the negotiation object and the operational negotiation framework are defined. Intelligent agents may use historical negotiation information, predictive analytics, Federated Learning models, and Digital Twin simulations to identify the most suitable renewable partners.

During the refinement phase, the participating entities exchange proposals and counterproposals regarding energy redistribution, storage allocation, delivery intervals, operational costs, and flexibility services. Intelligent agents dynamically adapt their negotiation strategies according to environmental changes and operational constraints.

In the final phase, the agreement is validated and transformed into an executable coordination contract. Digital Twin services and Edge AI mechanisms may supervise the execution of the negotiated agreement in real time in order to detect anomalies and maintain operational stability.

For each negotiation, the Intelligent Collaborative Agent manages one or several negotiation objects, the negotiation framework, and the associated coordination constraints. Global negotiation parameters may include negotiation duration, communication limits, candidate selection policies, coordination tactics, interoperability constraints, and adaptive communication protocols.

### 4.1. Collaborative Coordination Components

In order to manage the complexity of distributed renewable energy negotiations, the proposed framework introduces several coordination components responsible for supporting adaptive cooperation between autonomous renewable entities.

These coordination components facilitate distributed synchronization between simultaneous negotiations and dynamically manage operational dependencies between renewable participants.

The proposed coordination components are the following:

- Energy Allocation Component – manages the redistribution of renewable energy resources between autonomous participants through adaptive proposal exchange mechanisms.
- Reservation Component – ensures that a specific renewable resource or storage capacity is reserved entirely for a single operational request or participant.
- Adaptive Division Component – coordinates the partitioning of complex energy requests into multiple independent negotiation slots that may be processed simultaneously.
- Broker Component – automatically identifies suitable renewable participants and initializes negotiation processes according to operational objectives, energy forecasts, and system constraints.
- Transport and Synchronization Component – coordinates simultaneous negotiations involving shared transport infrastructures, energy routing mechanisms, or synchronized energy delivery operations.

Each coordination component can evaluate received proposals, validate operational constraints, and generate adaptive counterproposals according to the current state of the Renewable Energy Community.

From the coordination perspective, the proposed components may be classified into two categories.

The first category includes coordination components operating in a closed negotiation environment. These components rely only on the information associated with the current negotiation and manage constraints locally. Examples include the Energy Allocation Component, Reservation Component, and Adaptive Division Component.

The second category includes coordination components operating in an open negotiation environment. These components use information extracted from multiple simultaneous negotiations occurring throughout the renewable ecosystem. The Broker Component and the Transport and Synchronization Component belong to this category because they coordinate interactions across several distributed renewable entities simultaneously.

Unlike traditional negotiation architectures that only supervise isolated proposal exchanges, the proposed framework enables the coordination of complex distributed negotiations involving multiple autonomous renewable participants and heterogeneous operational constraints.

The novelty of the proposed architecture resides in the integration of intelligent coordination services, distributed negotiation mechanisms, Federated Learning models, Digital Twin simulations, and adaptive interoperability services within a unified collaborative framework dedicated to Renewable Energy Communities.

The proposed coordination infrastructure allows:

- synchronization of simultaneous negotiations,
- adaptive resource allocation,
- distributed decision-making,
- interoperability between heterogeneous renewable infrastructures,
- privacy preservation,
- and intelligent cooperation between autonomous renewable entities operating inside dynamic smart energy ecosystems.

## 5. Conclusions and Future Work

The rapid development of decentralized renewable energy infrastructures has created the need for intelligent coordination mechanisms capable of supporting adaptive cooperation between autonomous renewable entities. Renewable Energy Communities operate in highly dynamic environments characterized by fluctuating energy production, variable demand, heterogeneous infrastructures, and continuously evolving operational constraints. In this context, traditional centralized management approaches become increasingly difficult to apply efficiently.

This paper proposed an AI-driven collaborative framework dedicated to distributed coordination and automated negotiation inside Renewable Energy Communities. The proposed approach integrates Multi-Agent Systems, Federated Learning, Edge AI, Digital Twin technologies, and Explainable Artificial Intelligence in order to support intelligent interaction and adaptive decision-making between autonomous renewable entities.

The presented framework enables distributed renewable participants to exchange operational information, negotiate resource allocation, coordinate simultaneous interactions, and dynamically adapt their strategies according to environmental and operational conditions. Unlike centralized coordination architectures, the proposed approach preserves participant autonomy while improving interoperability, scalability, flexibility, and resilience inside smart renewable ecosystems.

Another important contribution of the paper is the integration of coordination components capable of supervising multiple simultaneous negotiations and managing dependencies between distributed renewable entities. Through intelligent coordination and adaptive negotiation mechanisms, the proposed architecture facilitates efficient cooperation between geographically distributed participants operating under heterogeneous constraints.

The integration of Federated Learning and Edge AI technologies improves privacy preservation and real-time responsiveness, while Digital Twin services enable predictive simulation and operational optimization before executing negotiated agreements in the physical infrastructure. In addition, Explainable Artificial Intelligence mechanisms contribute to improving transparency and trustworthiness in autonomous decision-making processes.

Future research directions will focus on extending the proposed framework through the integration of blockchain-based trust mechanisms, reinforcement learning strategies for adaptive negotiation, and predictive sustainability models for large-scale renewable ecosystems. Another important research direction concerns the implementation of fully autonomous coordination services capable of dynamically reorganizing renewable energy communities according to real-time operational conditions and market requirements.

The proposed framework represents a promising step toward the development of intelligent, interoperable, and sustainable smart energy ecosystems based on distributed Artificial Intelligence and autonomous renewable cooperation.

## References


- Ahmed, K., & Park, J. (2024). Adaptive AI models for renewable energy forecasting and optimization. Applied Energy, 357, 122484.
- Li, P., & Wang, T. (2023). Autonomous multi-agent coordination for decentralized energy trading in smart grids. Energy Reports, 9, 1120–1134.
- Wu, J., & Huang, Z. (2024). Parallel negotiation mechanisms for autonomous energy systems. IEEE Transactions on Smart Grid, 15(2), 1745–1758.
- Moreno, R., Silva, F., & Costa, E. (2025). Federated learning approaches for distributed renewable energy optimization. Computers in Industry, 158, 104020.
- Gupta, N., & Sharma, V. (2023). Edge AI services for intelligent distributed energy management. Renewable Energy, 205, 1187–1201.
- Chen, L., Zhao, M., & Xu, Q. (2024). Cloud-assisted intelligent coordination services for smart renewable infrastructures. Future Generation Computer Systems, 156, 214–229.
- Ferreira, L., Ramos, C., & Duarte, J. (2025). Digital Twin technologies for adaptive renewable energy ecosystems. Energy AI, 11, 100245.
- Kumar, S., Verma, A., & Singh, R. (2025). Interoperability challenges in decentralized smart energy systems. Sustainable Computing, 41, 100982.
- Santos, D., & Ferreira, P. (2023). Explainable AI mechanisms for autonomous renewable energy coordination. Journal of Cleaner Production, 389, 136102.
- Tolchinsky, S. Modgil, K. Atkinson, P. McBurney and U. Cortes, Deliberation dialogues for reasoning about safety critical actions. Autonomous Agents and Multi-Agent Systems, Vol. 25, Issue 2, pp. 209-259, 2012.
- Fujita, “Automated Negotiating Agent with Strategy Adaptation for Multi-times Negotiations”, chapter in Recent Advances in Agent-based Complex Automated Negotiation, Studies in Computational Intelligence, Vol. 638, pp 21-37, 2016.

- Caillere, S. Arib, S. Aknine, and C. Berdier, “A Multiagent Multilateral Negotiation Protocol for Joint Decision-Making”, chapter in Recent Advances in Agent-based Complex Automated Negotiation, Studies in Computational Intelligence, Vol. 638, pp 71 - 88, 2016.
- Lin and S. Kraus, “Can Automated Agents Proficiently Negotiate with Humans,” Communic. of the ACM, Vol. 53/1, pp. 78-88, 2010.
- Badica, S. Ilie, M. Kamermans, G. Pavlin, and M. Scafes, “Using Negotiation for Dynamic Composition of Services in Multi-organizational Environmental Management,” Environmental Software Systems. Frameworks of Environment, Vol. 359, pp 177-188, 2011.
- Penders, G. Pavlin, M. Kamermans, “A Collaborative Approach to Construction of Complex Service Oriented Systems.” Intelligent Distributed Computing IV. Studies in Computational Intelligence, vol. 315, pp. 55–66, Springer, 2010.
- Coutinho, A. Cretan, C.F. da Silva, P. Ghodous, and R. Jardim-Goncalves, “Service-based Negotiation for Advanced Collaboration in Enterprise Networks”, Journal of Intelligent Manufacturing, Volume 27, Issue 1, pp. 201–216, February 2016, DOI=10.1007/s10845-013-0857-4.
- -S. Li, R. Cabral, G. Doumeingts, and K. Popplewell, “Enterprise Interoperability Research Roadmap,” no. July. European Commision - CORDIS, p. 45, 2006.
- Jardim-Goncalves, A. Grilo, C. Agostinho, F. Lampathaki, and Y. Charalabidis, “Systematisation of Interoperability Body of Knowledge: the foundation for Enterprise Interoperability as a science,” Enterprise Information Systems, vol. 6, no. 3, pp. 1-26, 2012.
- Wang, Y. Xu, and M. Khanna, “A survey on the communication architectures in smart grid,” Computer Networks, Volume 55, Issue 15, 27 October 2011, pp. 3604-3629.
- H. Lasseter, “Smart Distribution: Coupled Microgrids,” Proceedings of the IEEE, 99(6), 1074–1082, 2011.
- Katiraei, R. Iravani, N. Hatziargyriou, and A. Dimeas, “Microgrids management,” IEEE Power and Energy Magazine, 6(3): 54-65, 2008.
- Camarinha-Matos L.M. and Afsarmanesh H., Collaborative Networked Organizations, 2004 Kluwer Academic Publisher Boston.
- Singh M.P., Commitments among autonomous agents in information-rich environments. In Proceedings of the 8th European Workshop on Modelling Autonomous Agents in a Multi-Agent World (MAAMAW), pages 141–155, May 1997.
- Cretan, A., Coutinho, C., Bratu, B., and Jardim-Goncalves, R., NEGOSEIO: A Framework for Negotiations toward Sustainable Enterprise Interoperability. Annual Reviews in Control, 36(2): 291–299, Elsevier, ISSN 1367-5788, 2012. http://dx.doi.org/10.1016/j.arcontrol.2012.09.010.
- Carrasco, L. Franquelo, J. Bialasiewicz, E. Galvan, R. Guisado, M. Prats, J. Leon, and N. Moreno-Alfonso, “Power electronic systems for the grid integration of renewable energy sources: A survey,” IEEE Trans. Power Electron., vol. 53, no. 4, pp. 1002–1016, Aug. 2006.
- Shahabi, M. R. Haghifam, M. Mohamadian, and S. A. Nabavi-Niaki, “Microgrid dynamic performance improvement using a doubly fed induction wind generator,” IEEE Trans. Energy Convers, vol. 24, no. 1, pp. 137–145, Mar. 2009.
- Kanchev, L. Di, F. Colas, V. Lazarov, and B. Francois, “Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications,” IEEE Trans. Ind. Electron., vol. 58, no. 10, pp. 4583–4592, Oct. 2011.
- A. Arefifar, Y.A-R I. Mohamed, and T. H. M. EL-Fouly, “Supply-adequacy-based optimal construction of microgrids in smart distribution systems,” IEEE Transactions on Smart Grid, vol. 3, no. 3, pp.1491-1502, Sept. 2012.
- S. Saleh, A. Althaibani, Y. Esa, Y. Mhandi, and A. A. Mohamed, "Impact of clustering microgrids on their stability and resilience during blackouts," 2015 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE), Offenburg, 2015, pp. 195-200.
- Bartolini, C., Preist, C., and Jennings, N., “A generic software framework for automated negotiation”, Technical Report HPL-2002-2, HP Laboratories Bristol.
- Singh., M. P., “Interaction-Oriented Programming: Concepts, Theories, and Results on Commitment Protocols”. In AI 2006: Advances in Artificial Intelligence, LNAI 4304, pp. 5 – 6, 2006.
- Bamford J.D., Gomes-Casseres B., and Robinson M.S., Mastering Alliance Strategy: A Comprehensive Guide to Design, Management and Organization. San Francisco: Jossey-Bass, 2003.
- Sycara K., Problem restructuring in negotiation, in Management Science, 37(10), 1991.
- Smith R., and Davis R., Framework for cooperation in distributed problem solving. IEEE Transactions on Systems, Man and Cybernetics, SMC-11, 1981.
- Zhang X. and Lesser V., Multi-linked negotiation in multi-agent systems. In Proc. of AAMAS 2002 July, Bologna, pg. 1207 – 1214.
- Barbuceanu M. and Wai-Kau Lo, Multi-attribute Utility Theoretic Negotiation for Electronic Commerce. In AMEC III, LNAI 2003, pg. 15-30.

- Keeny R. and Raiffa H., Decisions with Multiple Objectives: Preferences and Value Tradeoffs. JohnWilley & Sons, 1976.
- Bui V. and Kowalczyk R., On constraint-based reasoning in e-negotiation agents. In AMEC III, LNAI 2003, pp. 31-46.
- Faratin P., Automated component negotiation between autonomous computational agent. Ph.D. Thesis, Department of Electronic Engineering Queen Mary & West-field College, 2000.
- Cretan A., Coutinho C., Bratu B. and Jardim-Goncalves R., A Framework for Sustainable Interoperability of Negotiation Processes. In INCOM'12 $14^{th}$ IFAC Symposium on Information Control Problems in Manufacturing, 2011
- Vercouter, L., A distributed approach to design open multi-agent system. In $2^{nd}$ Int. Workshop Engineering Societies in the Agents' World (ESAW), 2000
- Muller H., Negotiation principles. Foundations of Distributed Artificial Intelligence, 1996.
- Hurwitz, S.M., Interoperable Infrastructures for Distributed Electronic Commerce. 1998, http://www.atp.nist.gov/atp/98wpecc.htm
- Ossowski S., Coordination in Artificial Agent Societies. Social Structure and its Implications for Autonomus Problem-Solving Agents, No. 1202, LNAI, Springer Verlag, 1999.
- Schumacher M., Objective coordination in multi-agent system engineering – design and implementation. In Lecture Note in Artificial Intelligence, No. 2093, Springer Verlag, 2001.
- Cretan, B. Bratu, C. Coutinho and R. Jardim-Goncalves, "A negotiation approach to support interoperability in a collaborative manufacturing environment," 2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC), Funchal, 2017, pp. 1282-1292.
- -M. Andreoli and S. Castellani, "Towards a Flexible Middleware Negotiation Facility for Distributed Components". In Proc. of "E-Negotiation" DEXA, Munich, Germany, 2001.
- Brandl, J-M Andreoli, and S. Castellani, "Ubiquitous negotiation games: a case study", Proc. of DEXA "e-negotiations" Workshop, Prague, Sep 1-5, 2003.
- Cretan, C. Coutinho, B. Bratu and R. Jardim-Goncalves, "A Negotiation Cloud-based Solution to Support Interoperability among Interconnected Autonomous Microgrids," 2018 International Conference on Intelligent Systems (IS), Funchal, Portugal, 2018, pp. 608-615, doi: 10.1109/IS.2018.8710579.