CH 07

MULTI-AGENT SELF-HEALING AND COLLECTIVE INTELLIGENCE IN MICROGRIDS WITH ELECTRIC VEHICLES

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ABSTRACT

This chapter develops a self-healing framework for modern distribution networks using multi-agent systems (MAS) specifically tailored to microgrids with high penetration of distributed generators (DGs) and electric vehicles (EVs). The proposed architecture follows a hierarchical structure – device, feeder, and microgrid manager agents – that enables decentralized fault management, network reconfiguration, and service restoration in radial and weakly meshed active distribution networks. EVs are treated as controllable vehicle-to-grid (V2G) resources that coordinate dynamically with DGs and storage units to support prioritized loads under emergency conditions and intentional islanding.
The overall self-healing process is decomposed into real-time fault detection, alarm dissemination, fault location identification, isolation decisions, flexibility offers from EV/DG agents, and multi-objective scheduling of restoration actions. Conceptual one-line diagrams, multi-microgrid layouts, and swim-lane flowcharts are used to illustrate the interactions among agents during disturbances and recovery. Recent research on MAS-based microgrid control and decentralized restoration suggests that this approach can shorten outages, increase restored load levels, and systematically exploit EV flexibility in smart-city environments.
Keywords: *Multi-agent systems (MAS), collective intelligence, self-healing, microgrids, V2G, active distribution networks, virtual power plant, smart-grid resilience*

INTRODUCTION

Conventional power systems were engineered around a one-directional energy flow: large centralized plants delivering electricity downstream through transmission and distribution networks to passive consumers. Over the past decade, this picture has changed dramatically. Distribution grids are evolving into decentralized, bidirectional energy networks populated with rooftop photovoltaics, small wind turbines, battery storage, and a growing range of controllable loads. These trends are driven by ambitious decarbonization policies, declining costs of distributed energy resources (DERs), and the pervasive digitalization of distribution networks.

Under these conditions, traditional centralized control architectures face structural limitations. As the number of controllable devices and the speed of system dynamics increase, centralized schemes struggle with scalability, communication bottlenecks, and vulnerability to single points of failure. At the same time, the growing variability and uncertainty introduced by DERs render classical protection and restoration strategies increasingly inadequate.

Microgrids have emerged as a key architectural response to these challenges. A microgrid can be viewed as a geographically bounded cluster of DGs, flexible loads, and storage systems, typically tied to a campus, community, or critical facility. Microgrids can operate either grid-connected or islanded, switching modes as needed to maintain local reliability and power quality. With high penetrations of rooftop PV, small wind, and other renewables, however, microgrids inherit the same issues of variability and uncertainty, making real-time control and restoration non-trivial.

In parallel, electric vehicles are transitioning from simple mobile loads to mobile energy assets through V2G technology. Uncoordinated charging can introduce new peaks, overload transformers, and deepen voltage problems in distribution feeders. Yet, when properly orchestrated, EVs can provide valuable services such as peak shaving, congestion relief, and—central to this chapter—support for self-healing actions in microgrids.

Multi-agent systems offer a natural computational paradigm to manage this complexity. In an MAS, many autonomous software agents, each with local sensing and decision-making capability, cooperate to achieve system-level goals. Instead of funneling all information to a central controller, MAS distributes intelligence across agents representing individual devices, feeders, and microgrid managers, enabling **collective intelligence** to emerge from their interactions.

In what follows, we introduce the foundations of MAS and collective intelligence in power systems, present a hierarchical agent architecture for self-healing microgrids with EV integration, and explain the coordination process for fault detection, isolation, and restoration. We then discuss coordination algorithms, software platforms, and co-simulation methods, and finally position MAS-based self-healing within the broader context of smart-city resilience and human-centered energy systems.

MULTI-AGENT SYSTEMS IN ENERGY NETWORKS

A **multi-agent system** consists of multiple interacting agents, each endowed with its own perception of the environment, local decision logic, and ability to act. In power systems, agents may represent distributed generators, loads, storage units, EV chargers, protection devices, or supervisory controllers, all linked through a communication infrastructure.

Four fundamental properties characterize agents in an MAS:

1. **Autonomy:** Each agent can make decisions without continuous human supervision, relying on local data and internal objectives.

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2. **Social ability:** Agents communicate and coordinate with one another—either peer-to-peer or via shared infrastructure—allowing them to collaborate on tasks that exceed the capability of any individual agent.
3. **Reactivity:** Agents monitor their environment and respond in near real time to events such as faults, load changes, or topology modifications.
4. **Proactiveness:** Beyond reacting, agents can plan and initiate actions to achieve longer-term goals, such as maintaining reserve margins or preparing for anticipated load peaks.

These characteristics make MAS particularly well suited to modern distribution networks, where devices are numerous, geographically dispersed, and subject to rapid changes in operating conditions. Agents make **local, context-aware** decisions while exchanging just enough information to maintain global consistency, thereby reducing dependency on a monolithic control center. In contrast, traditional centralized schemes must ingest large volumes of data and compute control actions for the whole network, which becomes impractical as network size and dynamics scale up.

In heavily loaded or faulted conditions, a well-designed MAS can help the system maintain continuity of service and security by coordinating local responses in a way that collectively achieves better outcomes than any isolated controller could. This emergent property—where the whole performs better than the sum of its parts—is at the heart of collective intelligence in power networks.

COLLECTIVE INTELLIGENCE AND SELF-HEALING

A **self-healing** power system is one that can autonomously detect faults, isolate affected components, and restore service as far as technically feasible, without relying on manual intervention. This capability is a defining manifestation of collective intelligence in smart grids. The self-healing process can be decomposed into three main phases:

1. **Fault detection:** Rapid identification that an abnormal condition—such as a short circuit, line outage, or protection misoperation—has occurred.
2. **Fault isolation:** Selective opening and closing of breakers and switches to separate the faulted section from the healthy network.
3. **Service restoration:** Reconfiguration of power flows, adjustment of DG outputs, dispatch of storage, and control of flexible loads to re-energize as many loads as possible while respecting operational limits.

In an MAS-enabled grid, agents contribute to each of these stages. Device-level agents continuously monitor local measurements (e.g., voltages, currents, breaker status) and raise alarms when anomalies are detected. Feeder or zone agents then aggregate and correlate these alarms to infer the likely location and nature of the fault, generate candidate isolation plans, and propose reconfiguration actions. A microgrid manager agent evaluates these proposals from a system-wide perspective, resolves conflicts, and issues final commands.

When collective intelligence functions effectively, the system converges to a **restored state** where critical loads are energized, technical constraints are satisfied, and preparedness for subsequent disturbances is enhanced. Agents representing DGs, storage systems, and EVs announce their available flexibility (e.g., surplus generation capability, discharge potential, or load-shedding options). Feeder agents then construct restoration plans that exploit this flexibility to maximize served load while keeping voltages and currents within allowable limits.

A simple illustrative scenario underscores the societal value of this approach. Consider a large-scale outage caused by a severe storm. In an MAS-enabled microgrid cluster, agents could automatically prioritize power to hospitals, water treatment plants, emergency communication centers, and community shelters, while temporarily curtailing non-critical loads. Neighboring microgrids might autonomously lend support to each other through tie-lines, exporting surplus power where it is most needed. Such adaptive, context-sensitive behavior would be extremely difficult to pre-program in a purely centralized framework, but emerges naturally when many agents coordinate under shared objectives.

MICROGRIDS, DISTRIBUTED GENERATORS, AND ELECTRIC VEHICLES

A **microgrid** is a localized segment of the distribution system that integrates DGs, controllable loads, and storage within a clearly defined electrical boundary. It typically serves a campus, industrial park, neighborhood, or critical infrastructure site and can operate either interconnected with the main grid or in islanded mode. Microgrids enhance resilience and flexibility but also introduce new challenges for protection, control, and restoration.

Common DG technologies in microgrids include rooftop and ground-mounted PV, small-scale wind turbines, microturbines, fuel cells, and diesel generators. These resources improve supply security and can reduce losses by generating closer to loads, but many of them—particularly solar and wind—are intermittent and weather-dependent. Battery storage helps smooth this variability, yet adds new dimensions such as state-of-charge management, degradation, and lifecycle cost.

Electric vehicles introduce another fast-growing class of flexible energy resources. At first glance, EVs appear as **large, potentially problematic loads**, especially when many vehicles charge simultaneously during evening hours. Uncoordinated charging can lead to voltage drops, transformer overloading, and increased distribution losses. However, with modern power electronics and control, EVs can play an active support role. Smart charging strategies can flatten peak demand, and V2G operation enables parked EVs to inject power back into the grid or microgrid when beneficial.

The interplay between microgrids, DGs, and EVs is central to MAS-based self-healing. Under normal operating conditions, agents managing EV charging, storage dispatch, and generation schedules collaborate to balance local supply and demand, improve efficiency, and reduce peak loads. During disturbances, these same agents dynamically **change roles**: EV agents may curtail charging or discharge energy to support stressed feeders, while DG agents ramp up generation within their operational limits. The hierarchical agent structure ensures that such actions remain aligned with system-level objectives.

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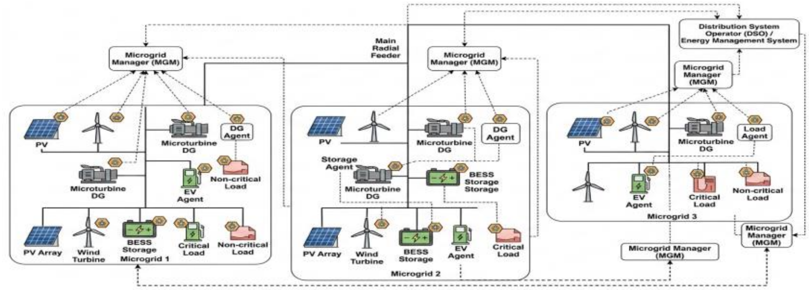

Figure 1. Conceptual Microgrid Topology with DG and EV Agents

Figure 1 illustrates a conceptual microgrid topology comprising DG units, storage systems, EV charging stations, and loads, each associated with its respective device agent and grouped under feeder and microgrid manager agents.

HIERARCHICAL MULTI-AGENT ARCHITECTURE FOR SELF-HEALING

To systematically exploit DG and EV flexibility for self-healing, we adopt a **three-layer hierarchical MAS architecture**:

1. **Device agents (bottom layer):** Each controllable asset—DG unit, battery system, controllable load, EV charger, or PV inverter—is equipped with a dedicated device agent. These agents measure local variables such as voltage, current, frequency, and state of charge, and send control commands to their associated equipment (e.g., active/reactive power setpoints, on/off signals, charging rates).
2. **Feeder or zone agents (intermediate layer):** Each feeder/zone agent oversees a defined section of the network and coordinates all device agents in that area. It collects measurements and alarms from its children, diagnoses local problems, and plans reconfiguration or repair strategies. This may include running fast optimization routines or rule-based logic to isolate faulty segments and reroute power flows while safeguarding critical loads.
3. **Microgrid manager agent (top layer):** The microgrid manager defines system-wide goals such as load prioritization, islanding policies, and economic or emission targets, and handles interactions with neighboring microgrids and the utility. During self-healing, it evaluates restoration plans proposed by feeder agents, resolves resource conflicts, and finalizes a coherent restoration strategy. If two feeders request support from the same set of DGs or EVs, for example, the manager allocates resources based on load criticality, contractual agreements, or fairness criteria.

This layered design mirrors human organizational structures, where local decisions are made quickly within a global strategic framework. It allows high-speed response at the device and feeder levels, while maintaining alignment with broader microgrid objectives through the manager agent.

Figure 2 depicts the hierarchical MAS architecture, showing the flow of information and commands between device, feeder, and microgrid manager agents.

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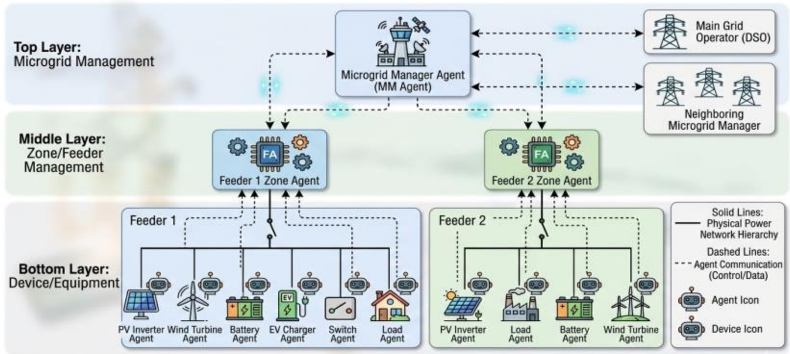

Figure 2. Hierarchical MAS Architecture for Microgrid Control and Self-Healing

SELF-HEALING COORDINATION PROCESS

Self-healing in an MAS-based microgrid unfolds as a sequence of structured interactions among agents. The process can be divided into three phases, which are illustrated in the swim-lane diagram of **Figure 3**.

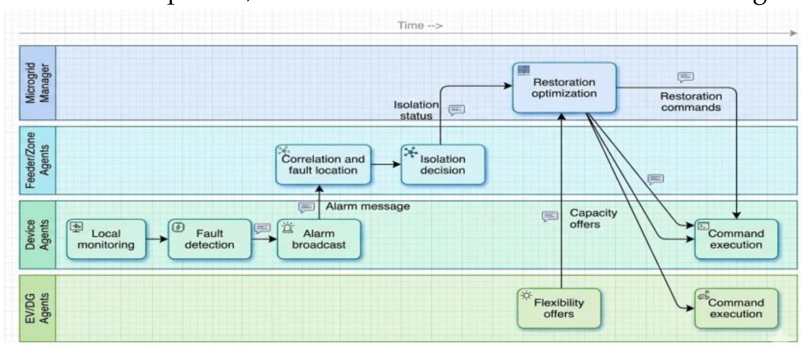

Figure 3. Self-Healing Workflow: Agent-Based Swim-Lane Diagram

Fault Detection and Alarm Dissemination

During normal operation, device agents continuously monitor local measurements and perform basic anomaly detection (e.g., threshold checks, pattern recognition). When an abnormal condition is observed—such as a sharp voltage dip, an overcurrent event, or frequent breaker operations—the device agent packages this information into an alarm message instead of streaming raw data to a central controller.

Each alarm message typically includes a time stamp, measured values, device status, and contextual information such as the physical location or asset identifier. The device agent forwards this structured alarm to its feeder agent, ensuring that emerging problems are detected quickly without saturating communication channels.

Fault Location and Isolation

Upon receiving alarms from one or more device agents, the feeder agent aggregates and correlates them to infer the probable faulted section. If several neighboring devices report anomalies at roughly the same time, the feeder agent consults network topology data, protection settings, and historical fault patterns to narrow down the fault location.

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Once a likely faulted segment is identified, the feeder agent formulates a set of candidate switching actions—for example, opening specific breakers or sectionalizing switches while closing alternative paths to preserve connectivity elsewhere. These candidate plans are sent to the microgrid manager agent, which evaluates their impact on the wider system, ensuring that no infeasible islands are created and that technical constraints remain satisfied.

After any necessary adjustments and conflict resolution, the manager agent ratifies a final isolation plan and sends executable commands back down to the relevant device agents. Breakers and switches are then operated accordingly, completing the fault isolation step.

Service Restoration with DGs and EVs

Once the fault is isolated, the focus shifts to **restoring service** to disconnected loads. At this stage, agents representing DGs, storage units, EVs, and loads actively participate in the restoration process.

- DG agents report their available active/reactive power, ramp rates, minimum on/off times, and operating costs.
- Storage agents share their state of charge, allowable charge/discharge power, and degradation constraints.
- EV agents provide their connection point, current battery state of charge, expected departure time, and user preferences such as minimum required charge.
- Load agents indicate their priority class (e.g., critical, high-priority, or non-critical) and flexibility options.

Feeder agents compile this information and construct local restoration optimization problems. Their goal is usually to maximize restored load—often with priority weights—subject to network constraints such as voltage bounds, line thermal limits, and device limits. Restoration actions may include reclosing previously opened lines, redispatching DGs, discharging storage, and commanding EVs to inject power or delay charging.

When multiple feeders compete for the same scarce resources (e.g., a limited pool of DG or EV capacity), the microgrid manager agent intervenes to coordinate allocations. It compares the local plans against global objectives and uses criteria such as critical load coverage or contractual rules to reconcile conflicts. The final system-level plan is then decomposed into specific setpoints and switching commands, which are sent to device agents for execution.

OBJECTIVE FUNCTIONS FOR SELF-HEALING OPTIMIZATION

The restoration problem is naturally expressed as a **multi-objective optimization** task. Typical objectives include reducing unserved energy, minimizing restoration time and operating cost, improving flexibility, and maintaining voltage and thermal constraints.

Table 1. Representative Objective Functions in MAS-Based Self-Healing

Objective	Description
Minimize unserved energy	Reduce the total energy demand that remains disconnected during and after the disturbance.
Minimize restoration time	Shorten the time required to reconfigure the network and restore service.
Minimize operating cost	Limit fuel and operational expenses of DG units and costs of energy imported from the main grid.
Improve flexibility index	Enhance the system's ability to cope with future disturbances by leveraging EVs, demand response, and storage.
Maintain voltage and thermal limits	Ensure that line currents, transformer loadings, and node voltages remain within allowable bounds.

These objectives may be combined through weighting factors, lexicographic priorities, or Pareto-based multi-objective optimization, depending on operator preferences. MAS implementations often distribute the optimization task across agents: feeder agents solve local sub-problems, resource agents enforce their own constraints, and negotiation protocols converge toward a feasible and near-optimal system-level solution.

ELECTRIC VEHICLES AS ACTIVE SELF-HEALING AGENTS

While EVs are frequently perceived as challenging loads due to their potential to exacerbate peaks under uncoordinated charging, MAS-based self-healing treats them as **active partners** in resilience. An EV agent typically includes three main components:

1. **Physical model:** Describes battery capacity, maximum charging/discharging power, round-trip efficiency, and network connection point.
2. **User preference model:** Captures driver requirements such as desired departure time, minimum acceptable state of charge, and sensitivity to tariffs or incentives.
3. **Decision logic:** Implements algorithms that reconcile mobility needs with grid-support objectives, deciding when to charge, pause, or discharge to the grid.

During normal operation, EV agents negotiate charging schedules with their feeder agents to avoid transformer overloads and excessive feeder loading. For instance, agents may agree to defer or modulate charging in exchange for lower electricity prices or other incentives. Simulation studies show that such coordinated strategies can significantly improve grid performance compared to purely price-driven or uncoordinated charging.

Under fault or islanding conditions, EV agents can **switch roles** from consumers to distributed energy resources. If their state of charge and driver schedule allow, they offer discharge services to support local loads, especially in critical locations such as hospitals or transport hubs. Each EV agent communicates its

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feasible power contribution and duration, and feeder and microgrid manager agents integrate these offers into the restoration optimization.

Benefits from EV participation in self-healing include:

- Localized support to nearby loads, reducing reliance on long-distance power transfers.
- Additional degrees of freedom in balancing supply and demand, making restoration plans more feasible.
- Ability to absorb surplus renewable generation during recovery, improving overall energy utilization.

Collectively, EV fleets behave like **distributed, mobile battery banks** that enhance the resilience, flexibility, and adaptability of the microgrid.

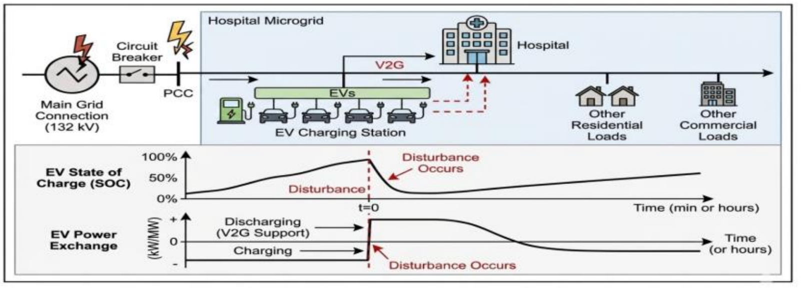

Figure 4. EV Vehicle-to-Grid Support During Disturbances

Illustrative graph suggestion: In the final book layout, you may add a graph showing "restored load vs. time" for two cases—(i) without EV support and (ii) with coordinated EV V2G—highlighting shorter restoration time and higher restored load in the MAS+EV scenario.

COORDINATION ALGORITHMS AND DECISION-MAKING METHODS

The **collective intelligence** of an MAS-based self-healing system arises from the local decision rules of individual agents and the protocols that govern their interactions. Three broad families of coordination methods are commonly used:

1. **Rule-based expert systems**
   - Encode operational knowledge using if–then rules, decision trees, or prioritized lists.
   - Example: a feeder agent might follow a rule such as "restore hospital feeders first, then water utilities, then commercial zones, and finally residential areas."
   - Predefined switching sequences can handle frequent contingency patterns, making the system easy to understand and implement, but potentially rigid in novel or high-dimensional scenarios.
2. **Optimization-based coordination**
   - Formulate self-healing as a constrained optimization problem with decision variables including switch states, DG and storage setpoints, EV charging/discharging powers, and load shedding choices.
   - Constraints enforce power balance, voltage and thermal limits, islanding feasibility, and operational bounds of devices.

- Multi-objective formulations incorporate unserved energy, restoration time, cost, and flexibility metrics.
- Distributed or hierarchical optimization (e.g., decomposition methods) allows agents to solve sub-problems locally and iteratively exchange information to reach consensus.

3. **Multi-agent reinforcement learning (MARL)**
   - Agents learn restoration strategies through repeated interaction with a simulated environment, receiving rewards that reflect restoration quality, cost savings, and constraint satisfaction.
   - Over many episodes, agents discover cooperative policies that may be difficult to design manually.
   - Hierarchical or federated MARL architectures improve scalability by limiting each agent's information requirements and preserving privacy.

A major challenge for any coordination method is **uncertainty**. Renewable generation, EV availability, load demand, and the communication network itself (delays, packet loss, cyber events) all introduce stochastic behavior. Researchers have proposed stochastic and robust optimization frameworks, as well as metaheuristic algorithms, to handle these uncertainties. MAS implementations can further leverage local forecasting and robustness margins maintained by individual agents, thereby reducing dependence on a single centralized forecast.

Table 2. Examples of MAS Applications in Distribution and Microgrid Self-Healing

System type	Key resources	MAS role in self-healing	Main benefits
Multiple microgrids in a distribution system	DGs, loads	Microgrid-level agents coordinate decentralized fault management and restoration.	Faster restoration, scalable resilience
Smart distribution network with microgrids	RES, EVs, loads	Agents couple energy management with self-healing under uncertainty.	Lower costs, losses, and voltage deviations
Active distribution feeder with EV fleets	RES, EVs, demand response	MAS orchestrates EV and demand flexibility during restoration.	Higher restored load, improved flexibility
Interconnected neighboring microgrids	RES, EVs, storage, loads	Zone agents coordinate support and tie-line reconfiguration.	Reduced restoration time, better local use
Dynamic microgrid formation on active feeders	DGs, loads	Agents form and control temporary microgrids during faults.	Maximal load restoration, lower DG cost

MAS PLATFORMS AND CO-SIMULATION

Translating MAS-based self-healing concepts into **working prototypes** requires both an agent software platform and integration with power-system simulators.

A widely used MAS platform is the **Java Agent Development Framework (JADE)**. JADE supports standardized agent registration, life-cycle management, and inter-agent communication following FIPA specifications. Each agent is implemented as a Java object that can run on distributed machines, register with a directory facilitator, and exchange structured messages. Device, feeder, and manager agents can be instantiated as JADE classes with behaviors defined through Java code.

Because software agents alone cannot capture physical grid behavior, **co-simulation** with power-system tools is essential. One common approach couples JADE with MATLAB/Simulink, OpenDSS, or DIgSILENT via middleware. At each simulation step, the power-system tool computes the electrical state (e.g., bus voltages, line currents, power flows) given the current control setpoints. These results are passed to the agent platform, where agents process the information and determine new actions, which are then fed back to the power simulator. This bidirectional exchange continues over time, enabling detailed evaluation of MAS strategies under realistic conditions.

Co-simulation frameworks offer several advantages:

- They allow different MAS strategies to be tested under identical disturbance scenarios.
- They enable sensitivity studies with respect to EV penetration, renewable variability, and communication network performance.
- They can incorporate cyber-security models and even human-in-the-loop agents for operator validation.

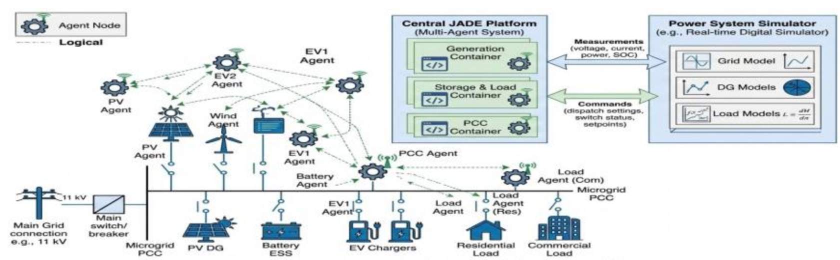

Figure 5. Agent Communication Network and Co-Simulation Architecture in a Microgrid

Illustrative diagram suggestion: For the final book chapter, you may include a block diagram showing three coupled layers: (i) physical microgrid model (e.g., in Simulink), (ii) MAS platform (e.g., JADE) with device/feeder/manager agents, and (iii) communication network model.

SMART CITIES AND HUMAN-CENTERED ENERGY SYSTEMS

Although the preceding sections have focused primarily on technical design, self-healing microgrids function within **broader urban and social contexts**. In smart cities, electrical resilience is tightly linked to public safety, economic activity, and quality of life. Prolonged outages can disrupt healthcare, transportation, water supply, and communication services, with disproportionate impacts on vulnerable communities.

Microgrids supported by MAS-based self-healing and EV flexibility can enhance urban resilience in several ways. First, they promote **decentralization**, allowing local networks to island and restore power even when centralized control centers are overloaded or disconnected. Second, the multi-agent framework enables explicit encoding of **social priorities**: agents can be configured to first restore power to hospitals, water treatment plants, emergency services, and community shelters before serving less critical loads. Third, distributed EV fleets effectively become a **city-wide mobile storage resource**, parking in different neighborhoods and providing localized support where it is most needed during emergencies.

Human participation is integral to this picture. EV owners are not merely passive consumers but potential **co-providers** of resilience. Appropriately designed tariffs, contracts, and community programs can incentivize vehicle owners to authorize V2G participation during critical events.

Equity considerations must be explicitly incorporated into MAS-based self-healing logic. Low-income neighborhoods and marginalized populations often experience the longest and most damaging outages. Targeted deployment of microgrids, renewables, storage, and EV infrastructure in these areas—combined with agent-based policies that prioritize their essential services—can help close resilience gaps. In this way, multi-agent architectures function not only as technical control solutions, but also as tools for embedding fairness and social values into the design of future energy systems.

CONCLUSION AND FUTURE DIRECTIONS

Microgrids enriched with DGs, storage, and EVs are reshaping the structure and operation of distribution networks. The very features that make them flexible and sustainable—decentralization, variability, and high controllability—also challenge conventional centralized control and restoration methods. Multi-agent systems provide a compelling framework for organizing decision-making in such environments, distributing intelligence among device, feeder, and microgrid manager agents and relying on **collective intelligence** rather than rigid central commands.

This chapter has presented a MAS-based approach to self-healing microgrids with EV integration. After outlining the basics of MAS and collective intelligence, we introduced a hierarchical architecture, walked through the self-healing process, and highlighted the crucial role of EVs as active, flexible agents. We reviewed coordination methods ranging from rule-based heuristics to multi-objective optimization and MARL, and discussed implementation via JADE-based co-simulation with power-system tools. Finally, we placed these ideas within the broader vision of smart cities, emphasizing how agent-based self-healing can support resilience, equity, and citizen engagement.

Promising directions for future work include deeper integration of advanced AI techniques, richer models of EV behavior and user preferences, and scalable distributed optimization methods with formal privacy guarantees. Large-scale field demonstrations and real-time laboratory experiments in urban settings will be crucial to validate these concepts, refine regulatory frameworks, and demonstrate robust economic value. Collectively, these developments can help realize power systems that are not only more efficient and flexible, but also more resilient and responsive to the needs of the communities they serve.

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