

Embodied Intelligence for Safer Power-System Field Operations: A Critical Review of Technologies, Applications, and Challenges

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Abstract

Modern power grids require safer and more reliable field operations, yet conventional robots often face limitations in unstructured environments because of rigid pre-programming and weak perception–action coupling. This review examines Embodied Intelligence (EI) as an emerging direction for enhancing power-system field operations. We first evaluate the environmental adaptability of morphological carriers, including quadrupeds, humanoids, and unmanned aerial vehicles, and then define the perception–cognition–execution closed-loop architecture used in this review. Three application domains are then examined. Intelligent inspection focuses on active perception and potential open-vocabulary object detection. Live-line maintenance emphasizes Sim-to-Real methods and shared autonomy, while disaster-response applications involve heterogeneous air–ground robotic coordination. The review also discusses the potential for EI to reduce human exposure to hazardous tasks and influence labor structures, while a regional text-based proxy illustrates differences in policy attention to digital infrastructure. Finally, we analyze major constraints, including hardware endurance under extreme climates, edge-computing latency, foundation-model uncertainty and hallucination, cybersecurity, and safety certification. Overall, EI should not be interpreted as a mature replacement for current utility practice; it is a developing technological direction whose safe deployment will require field validation, standardized evaluation, cybersecurity assurance, and continued human supervisory authority.

Keywords: embodied intelligence; power grid operations; autonomous robotics; intrinsic safety; sim-to-real transfer; intelligent inspection; employment structure; social justice



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1. Introduction

1.1. Research Background and Literature Review

The global imperative to ensure the reliability and resilience of modern power grids has intensified the focus on upgrading and securing power system field operations [1–3]. Within this domain, field operations, encompassing live-line maintenance, high-altitude tasks, and post-disaster emergency repairs, represent a critical and highly hazardous frontier [4,5]. According to occupational safety statistics, electrical incidents and falls in harsh environments remain leading causes of fatal workplace injuries in the utility

sector [6,7]. In response, national strategies and industry mandates, such as China's "14th Five-Year Plan for Modern Energy System" and the IEEE/IEC safety modernization standards, support a transition toward "intrinsic safety", aiming to minimize casualties and advance intrinsically safer operations through unmanned and shared-autonomy solutions. While robotics has emerged as the leading pathway to achieve this, the rapid deployment of traditional power system robots introduces a pivotal yet disruptive bottleneck to the ongoing modernization of the grid [8–10].

Although essential for reducing human casualties, the widespread application of traditional automation faces formidable challenges when confronted with the realities of power system environments [5,7]. Unlike structured manufacturing floors, the grid imposes extreme unstructuredness and dynamic physical changes. For instance, live-line maintenance requires task-specific positioning, sensing, and contact control while maintaining the electrical clearances prescribed for the selected work method, voltage level, tooling, and applicable safety rules. Post-disaster emergency response, by contrast, may require navigation through collapsed towers, mud, debris, and damaged energized assets. Traditional automation, heavily reliant on pre-programmed kinematic trajectories, static SLAM (Simultaneous Localization and Mapping), and rigid rule-based logic, lacks the cognitive adaptability for these chaotic scenarios [11,12]. Such systems have limited semantic reasoning and generalization to unseen anomalies [13]. Field deployments show that basic wheeled robots can perform routine substation readings, but environmental variation may interrupt navigation or sensing, while autonomous physical intervention and complex fault resolution remain limited [8,10,14].

Based on this, the existing literature has increasingly focused on the deployment of intelligent autonomous systems in power grids. However, the resulting research often approaches the challenge from a component-centric or siloed perspective, focusing on discrete aspects like isolated computer vision algorithms for defect detection or purely mechanical manipulator designs. These valuable yet piecemeal studies leave a critical gap: they lack a holistic, strategic framework that charts the evolutionary pathway from rigid automation to systemic, autonomous physical interaction. To break through this bottleneck, this paper introduces Embodied Intelligence (EI) [15–17], the profound fusion of advanced cognitive "brains" (e.g., large foundation models) and versatile physical "bodies", as an emerging integrated technological paradigm. To clearly articulate this transition, this paper constructs a structured critical review framework based on the logical progression of "Conceptual Architecture, Core Application Scenarios (Inspection, Maintenance, Emergency), Comprehensive Benefits and Challenges." Within this framework, the reviewed studies are organized according to their degree of relevance to power-system field operations, including direct grid studies, utility-relevant autonomous precursors, and transferable general robotics enablers. This framework examines how EI may extend grid operations while identifying both potential safety benefits and unresolved deployment constraints. The main contributions of this paper are as follows:

- (1) The conceptual architecture of Embodied Intelligence within power systems is systematically defined. By analyzing the fundamental limitations of traditional robotics, this paper elucidates the potential role of EI in power system, detailing the "perception–cognition–execution" closed-loop technical architecture. It further evaluates the adaptability of various physical carriers, such as quadrupedal robots, bipedal humanoids, and dexterous manipulators, discussing their potential morphological advantages in unstructured grid environments.

- (2) This study critically reviews EI applications and enabling robotic technologies in power systems. It then organizes the implementations by operational depth and environmental complexity. The reviewed studies are organized into direct power-grid evidence,

utility-relevant precursors, and transferable general robotics enablers. This framework evaluates state-of-the-art advancements in three core scenarios: intelligent inspection (autonomous perception and potential open-vocabulary defect recognition in unstructured environments), live-line maintenance (dexterous manipulation, Sim-to-Real transfer, and human–robot collaboration in high-risk zones), and emergency response (rapid situational support, dynamic risk assessment, logistics, and limited physical intervention during extreme disasters).

(3) A comprehensive evaluation of the socio-economic benefits, promotion bottlenecks, and future outlook of EI is provided. Beyond technical and economic gains, this paper highlights the profound social impacts, particularly how EI may gradually reshape the employment landscape of the power sector by substantially reducing human exposure to high-risk, extreme environments. Furthermore, it critically analyzes current bottlenecks, including hardware reliability, the safety-critical risk of large-model “hallucinations” in high-stakes operations, and edge-computing latency, and charts future research directions, emphasizing the development of domain-specific embodied foundation models for power systems and air–ground heterogeneous robotic swarms.

1.2. Review Scope and Methodology

This structured critical review was updated in June 2026 using Web of Science, Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The core search logic, adapted to the syntax of each database, combined power-domain terms with embodied-robotics terms. The primary time window was 2015 to June 2026, while earlier seminal works were retained only when required for foundational concepts. A component-level study was retained only if it met three conditions. First, the method had to be evaluated on a physically embodied robotic platform or in a physically grounded closed-loop setting. Second, it had to provide identifiable evidence on perception, cognition/planning, execution/control, or their integration. Third, it required either direct power-grid relevance or an explicitly justified transfer pathway to inspection, live-line maintenance, or emergency response. Standalone vision, locomotion-control, or sensor studies were excluded when they were evaluated only as isolated algorithms or devices without embodied validation and operational relevance. Candidate works were screened by title and abstract and then assessed at full-text level against these criteria, yielding a final set of 125 retained works. During synthesis, each work was coded by its principal functional coverage: perception, cognition/planning, execution/control, or an integrated closed loop connecting at least two layers through physical feedback. Because the literature is heterogeneous in terms of task definition, platform, dataset, and validation environment, this article is a structured critical review rather than a registered systematic review or formal meta-analysis; no formal risk-of-bias instrument or PRISMA record-flow accounting was applied. The retained works were also organized by evidence role as direct power-grid studies, utility-relevant autonomous precursors, and transferable general robotics enablers, as summarized in Table 1.

Table 1. Descriptive summary of the reviewed literature.

Dimension	Category	Count
Publication period	≤2019	21
	2020–2022	22
	2023–2026	82

Table 1. *Cont.*

Dimension	Category	Count
Source type	Journal articles	95
	Conference/workshop/proceedings papers	15
	Preprints/Book chapters/Others	15
Major venue/publisher family	IEEE family	41
	Elsevier/Cell family	15
	Springer Nature family	23
	MDPI	12
	Others	34
Evidence-role assignments (non-mutually exclusive; one study may receive multiple roles)	Direct power-grid studies	33
	Utility-relevant autonomous precursors	66
	Transferable general robotics enablers	72

2. Concept and Architecture of Embodied Intelligence

This section focuses strictly on the technological essence of EI. Before exploring its specific field applications in power systems in Section 3, it is imperative to establish a robust theoretical and technical framework. This chapter first defines the core paradigm of EI, subsequently deconstructing it into its two foundational pillars: the physical architecture and the cognitive architecture. By examining these components, this section demonstrates how they synergize to form a cohesive, highly adaptable system capable of autonomous operation in complex environments.

2.1. Core Concept: Brain–Body Integration

The essence of EI lies at the profound intersection of Artificial Intelligence (AI) and advanced robotics. Refs. [15,16] explicitly state that EI is neither purely software-based AI, which inherently lacks physical agency and the capacity to intervene in the real world, nor is it traditional robotics, which typically lacks high-level semantic understanding and relies heavily on rigid pre-programming. Instead, it represents a paradigm shift toward a “Brain–Body” fusion, wherein a cognitive “brain” learns through continuous physical interaction with its environment and controls a morphological “body” to execute complex tasks [17–19]. In ref. [20], the embodied cognitive framework was proposed to address the symbol grounding problem in AI, demonstrating that true intelligence emerges only when an agent can physically interact with its surroundings. This interaction generates multi-modal sensory feedback that anchors abstract computational concepts into tangible physical realities, enabling the system to perceive, reason, and act autonomously. In this review, VLA models and large foundation models are treated as representative contemporary realizations of EI rather than mandatory definitional prerequisites. A study is considered directly EI-relevant only when it involves a physically embodied agent coupled with an integrated closed loop linking multimodal perception, task-level cognition or decision-making, and action execution. By contrast, systems that provide autonomous mobility, inspection, or teleoperation without such integrated task-level reasoning are discussed as robotic or autonomous precursors, rather than as full EI implementations. This distinction is adopted throughout the following sections to maintain conceptual consistency.

For evidence classification, direct power-grid studies report validation on grid assets, sites, or operational tasks; utility-relevant autonomous precursors demonstrate autonomous functions in grid-adjacent or comparable environments without the complete perception–cognition–execution loop; and transferable general robotics enablers contribute

perception, planning, control, locomotion, or manipulation methods without grid-specific validation. Categories may overlap when a study serves more than one evidentiary role.

In the specific context of power systems, this paradigm shift represents a promising direction for addressing longstanding technological bottlenecks. Traditional grid robots have not yet achieved widespread autonomous deployment in unstructured environments because many architectures separate perception, planning, and action [21,22]. Based on this, refs. [23,24] analyze the operational cases of traditional wheeled inspection robots in substations, pointing out that these systems rely heavily on predefined semantic maps and deterministic waypoints. When confronted with environmental anomalies, such as a temporarily parked maintenance vehicle, a dropped tool, or terrain altered by extreme weather, these robots lack the semantic reasoning required to adapt, which can result in task interruption or failure. Embodied Intelligence addresses this critical limitation by enabling systems to genuinely “understand” the chaotic, dynamic reality of power operations. By coupling advanced cognitive reasoning with physical execution [15–17], an EI system can adaptively navigate unexpected obstacles, recognize the functional intent behind grid components, and dynamically adjust its operational strategy.

2.2. Physical Architecture: Morphological Carriers and Environmental Adaptability

Having defined the core concept, it is essential to first examine the physical forms, the morphological carriers, that this intelligence utilizes to interact with the physical world of the power grid. As illustrated in the conceptual schematic of Figure 1, the physical architecture is not merely a passive vehicle; its morphological design directly dictates the system’s environmental adaptability, its kinematic limits, and the upper bounds of its task execution capabilities [25,26].

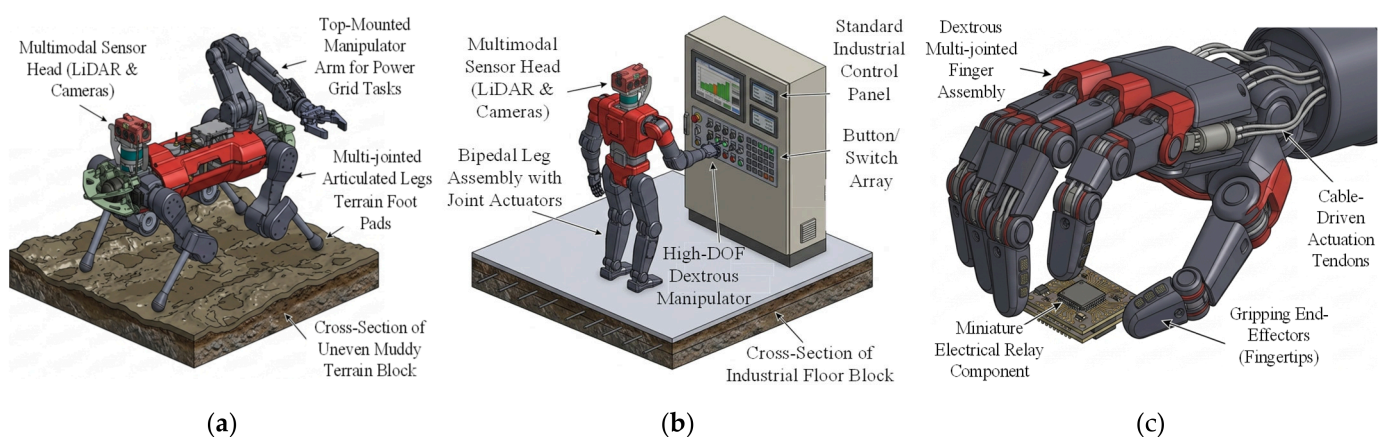


Figure 1. Conceptual illustration of three representative physical carrier morphologies discussed in this review: (a) a quadrupedal platform for uneven outdoor terrain; (b) a humanoid platform for human-oriented infrastructure interaction; and (c) a dexterous robotic hand for fine manipulation. The figure is schematic and does not represent a specific validated system from the cited literature.

To address the severe challenges posed by unstructured terrains, quadrupedal platforms have emerged as the foundational agile base of the EI system. Power grid environments, particularly post-disaster zones, active construction sites, or aging outdoor substations, are characterized by chaotic, uneven, and often muddy terrains that can restrict the deployment of conventional wheeled or tracked robots [27–29]. Ref. [29] states that quadrupedal robots, leveraging advanced deep reinforcement learning (DRL) algorithms, provide the necessary mobility to navigate these chaotic environments. In ref. [30], a hierarchical motion planning system was proposed to enable the safe, autonomous navigation of quadruped robots in cluttered outdoor grid sites, using front-end kino dynamic search and

back-end B-spline optimization with iterative time-allocation refinement. These studies endow the EI system with high-frequency dynamic stability without over-relying on fragile visual odometry. However, an objective analysis of current quadrupedal research reveals significant structural limitations. Ref. [31] points out that while quadrupeds possess exceptional macroscopic mobility, their payload capacity and manipulation reach are inherently constrained. When a quadruped carries a top-mounted manipulator, the added payload and altered center of mass can couple locomotion and manipulation performance. The resulting effects on stability, reach, workspace, and positioning accuracy depend on arm mass, mounting geometry, gait, terrain, and controller design; no universal quantitative penalty can therefore be inferred.

Consequently, bipedal humanoid robots may offer morphological compatibility with infrastructure designed around human dimensions, but their suitability is task-dependent; it suitability depends on mobility, payload, energy use, stability, tooling, and the operating environment [32,33]. The fundamental rationale for deploying humanoids in power systems is that the entire infrastructure, ranging from the height of control panels and the pitch of substation staircases to the ergonomic design of maintenance tools, was explicitly engineered for human dimensions and kinematics [34]. Ref. [35] argues that utilizing a developmental curriculum learning approach enables humanoids to acquire robust gaits, overcoming complex control dynamics to reliably navigate unpredictable outdoor power grid environments. In ref. [36], a hybrid predictive controller considering full-body dynamics was proposed to solve the problem of executing agile locomotion maneuvers, demonstrating that humanoids can traverse unstructured terrains during critical power grid inspections. Despite these morphological advantages, the application of bipedal humanoids faces severe technical bottlenecks [37,38]. Their energy efficiency, often evaluated using Cost of Transport, may be lower than that of wheeled or quadrupedal systems under some conditions; however, any comparison depends on gait, speed, payload, terrain, and controller design and should not be treated as a universal platform ranking. Furthermore, maintaining dynamic balance while executing heavy-duty power grid tasks, such as pulling stiff high-voltage cables or operating rusted mechanical disconnect switches, introduces massive external disturbance forces. Current humanoid joint actuators and balancing algorithms struggle to counteract these forces reliably, posing a risk of unsafe falls in high-voltage areas.

Beyond macroscopic locomotion, the execution of power grid operations relies heavily on dexterous manipulators for high-fidelity physical interaction [39,40]. Multi-fingered dexterous hands and highly articulated robotic arms serve as the critical physical interface for high-voltage, high-precision tasks [41]. Ref. [42] introduces a novel hand-object interaction representation for dexterous manipulation, enabling the “body” to execute delicate interventions, such as grasping diverse tools, replacing small fuses, or operating complex diagnostic instruments. In ref. [43], an imitation learning framework for dexterous manipulation was proposed to solve the problem of operating in unstructured environments, a technique directly applicable to the maintenance of power equipment. However, the adaptability of these dexterous end-effectors in power grids is currently constrained by harsh environmental factors. The high-electromagnetic interference (EMI) environments typical of ultra-high-voltage (UHV) substations can severely disrupt the signal transmission of delicate capacitive or piezoresistive tactile sensors embedded in robotic fingertips [44,45]. Additionally, the mechanical durability of tendon-driven multi-fingered hands remains insufficient for the high-torque, repetitive tasks required in grid maintenance, indicating a necessary and ongoing trade-off between kinematic dexterity and industrial robustness within the physical architecture.

2.3. Cognitive Architecture: The “Perception–Cognition–Execution” Closed Loop

With the physical carriers established, EI requires a software and algorithmic architecture that links perception, decision-making, and physical execution. Figure 2 provides a high-level conceptual representation of this perception–cognition–execution loop. In probabilistic terms, $P(\text{Action} | \text{Sensory Input})$ denotes a conditional distribution over action tokens or low-level commands given the agent’s multimodal observation history and task context. The figure is not intended as a complete certification architecture. Safety-critical deployment would additionally require explicit state estimation and memory, task and motion planning, uncertainty assessment, runtime safety monitoring, human supervisory authority, and independently verified low-level control.

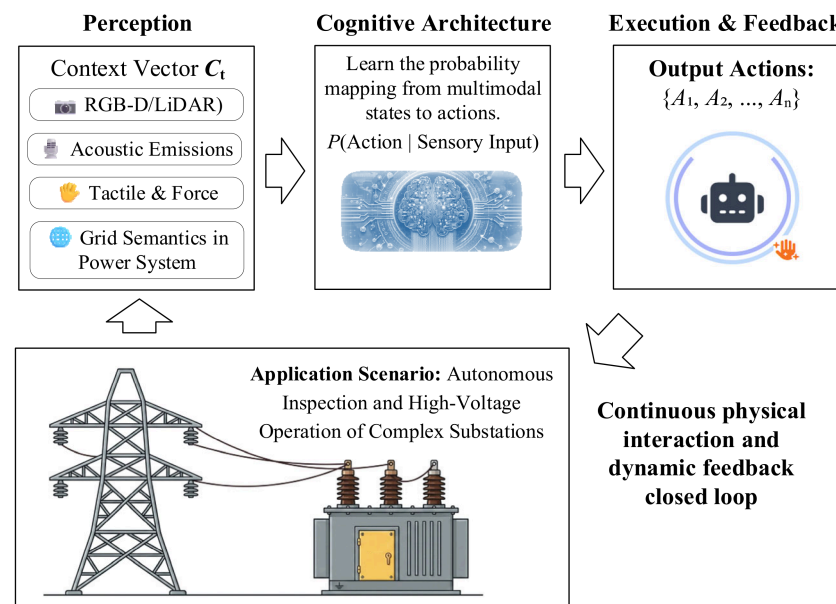


Figure 2. Conceptual high-level representation of the perception–cognition–execution loop in EI. State estimation, memory, planning, uncertainty assessment, runtime safety supervision, human oversight, and verified low-level control are complementary deployment layers and are not fully represented in this simplified schematic.

First, the foundation of this cognitive architecture is the multi-modal perception layer [46,47]. The physical “body” feeds massive streams of environmental data to the “brain” through integrated vision (RGB-D cameras, LiDAR), acoustic (microphone arrays), and tactile sensors, creating a high-dimensional, semantic understanding of the grid environment [48,49]. Ref. [47] explicitly states that multi-modal sensor fusion is critical for embodied agents to resolve ambiguities in complex, visually degraded environments. For instance, in ref. [50], a Transformer-based multi-modal fusion recognition algorithm integrating visible, infrared, and hyperspectral imaging was developed to enhance equipment identification in complex substation environments, effectively addressing the limitations of unimodal vision in cluttered backgrounds. Similarly, in ref. [51], a dual-modal approach combining time-series waveforms with phase-resolved partial discharge patterns was introduced to improve the classification of discharge types in switchgear, providing a hardware-robust solution that mitigates the impact of environmental noise and signal variations. Furthermore, in ref. [52], a Fusion Convolutional Network merging UAV-captured imagery with leakage current data was proposed for real-time insulator monitoring, demonstrating that the synergy of visual features and electrical parameters significantly boosts accuracy in identifying surface contamination under diverse outdoor illumination conditions. Collectively, these studies underscore that multi-modal fusion is essential for

overcoming the inherent sensing limitations of single-source data, thereby ensuring the reliability and intelligence of critical power system inspection tasks.

Meanwhile, at the core of the cognitive architecture are Embodied Foundation Models, which serve as the central reasoning processor. The recent emergence of Vision–Language–Action (VLA) models has expanded how robots process information and interact with the world [53,54]. Ref. [55] demonstrates that VLA models can directly map multi-modal sensory inputs and natural language instructions to low-level robotic action tokens. In principle, such models may support semantic interpretation and open-vocabulary perception and task-conditioned reasoning, although grid-specific validation remains limited. For example, if a human operator issues a natural language command to “isolate the faulty breaker on the left,” a VLA-based system would need to identify the specific breaker, reason about the necessary sequence of physical steps, and generate candidate actions subject to verified safety constraints and human supervisory authority. In ref. [56], a dual-memory augmented VLA framework named Optimus VLA was proposed to solve the problems of low inference efficiency and poor temporal robustness in robotic manipulation, enabling faster action generation and superior task consistency by integrating global task-level priors with local execution history.

The following formulations are representative notation anchors for methods cited in this review; they do not constitute a unified power-system EI model or a standardized cross-study benchmark. A B-spline trajectory representation used in motion planning [30] can be written as

$$\mathbf{p}(\tau) = \sum_{i=0}^n N_{i,d}(\tau) \mathbf{c}_i \quad (1)$$

where $\mathbf{p}(\tau)$ is the m -dimensional trajectory position at the normalized parameter $\tau \in [0, 1]$; $N_{i,d}(\tau)$ is the i -th B-spline basis function of degree d ; and $\mathbf{c}_i$ is the i -th m -dimensional control point. The index $i = 0, \dots, n$ therefore represents $n + 1$ control points. In trajectory optimization, $\mathbf{c}_i$ and the time allocation are adjusted subject to boundary, kinematic, and obstacle-avoidance constraints.

For learning-based embodied control, a representative DRL objective used in locomotion studies [29,35] is

$$a_t \sim \pi_{\theta}(\cdot | s_t), \max_{\theta} E_{\pi_{\theta}} \left[\sum_{k=0}^{T-1} \gamma^k r_k \right] \quad (2)$$

where s_t is the state and a_t is the action at time step t ; a_t is sampled from the policy $\pi_{\theta}(\cdot | s_t)$, whose parameters are θ . The quantity r_t is the reward at step t , T is the final index of the return horizon, $\gamma \in (0, 1]$ is the discount factor, and $E_{\pi_{\theta}}$ denotes expectation under the policy. The maximization over θ seeks policy parameters that maximize the expected discounted return. For quadruped locomotion, r_t may combine velocity tracking, posture stability, energy consumption, and collision avoidance with application-specific weights.

The VLA-style conditional action-generation mapping discussed in refs. [55,56] can be represented as

$$a_{t:t+H-1} \sim P_{\theta}(\cdot | o_{1:t}, \ell) \quad (3)$$

where $o_{1:t}$ is the multimodal observation history available through time t ; ℓ is the task instruction or semantic context; $a_{t:t+H-1}$ is the action sequence generated over the next H steps; P_{θ} is the conditional distribution parameterized by θ ; and the symbol $\sim$ indicates that the action sequence is sampled or generated from this distribution. Depending on the implementation, $a_{t:t+H-1}$ may represent action tokens, end-effector targets, or low-level control commands.

For Lyapunov-based safety or stability regularization, a representative sufficient decrease condition is:

$$\dot{V}(x(t)) \leq -\alpha V(x(t)), \alpha > 0 \quad (4)$$

For whole-body locomotion and motion planning, the finite-horizon MPC formulation used in related work can be written as:

$$\begin{cases} \min_{u_0, \dots, u_{H-1}} \sum_{k=0}^{H-1} \left[(x_k - x_k^{ref})^T Q (x_k - x_k^{ref}) + u_k^T R u_k \right] + (x_H - x_H^{ref})^T P (x_H - x_H^{ref}) \\ x_{k+1} = f(x_k, u_k), x_0 = x(t), x_k \in X, u_k \in U, k = 0, \dots, H-1 \end{cases} \quad (5)$$

Therefore, Equations (1)–(5) are included only as representative mathematical templates linked to the cited method families. They are not proposed as a unified EI framework, and their objectives, constraints, parameter values, datasets, and implementation details remain application-specific; accordingly, they are not used as cross-study performance measures in this review.

Finally, the cognitive architecture is completed by the execution and physical feedback loop. The cognitive decisions generated by the foundation models must be translated into high-frequency, low-level physical actions by the morphological carriers discussed in Section 2.2. Crucially, the physical interaction is not a one-way command execution but a continuous, dynamic feedback process [57,58]. When the robotic hand grasps a switch, the tactile and force-torque feedback is instantly routed back to the cognitive layer, allowing the system to verify task success or dynamically adjust its grip force if the switch is jammed [59,60]. This continuous feedback loop ensures that the system constantly learns from its physical interventions, dynamically adjusting its cognitive models based on real-world physical outcomes. This robust “Perception–Cognition–Execution” architecture not only defines the current state of Embodied Intelligence but also provides the indispensable technological foundation for the specific, high-complexity field applications in power systems that will be explored in Section 3.

3. Applications of Embodied Intelligence in Field Operations of Power System

Building on the technical architecture described in Section 2, this section examines three application areas of EI in power-system field operations: intelligent inspection, live-line maintenance, and emergency response. The reviewed evidence includes direct power-grid studies, utility-relevant autonomous precursors, and transferable methods from general robotics. These categories indicate how each study contributes to the review and may overlap. Because the studies differ in task definition, robotic platform, dataset, validation environment, and reported metrics, their results are not directly comparable. Table 2 therefore provides a qualitative synthesis of current practices, potential EI-enabled capabilities, evidence maturity, and key limitations. It should not be interpreted as a standardized performance benchmark or a formal technology-readiness assessment.

Table 2. Conceptual comparison of current utility practice and potential EI-enabled capabilities across inspection, live-line maintenance, and emergency response.

Operational Domain	Existing Utility Practice	What EI Adds	Evidence Maturity
Inspection	Manual patrols; wheeled robots; conventional UAV imaging	Active perception; semantic anomaly reasoning; adaptive navigation	Partly validated in grid inspection; advanced cognition still emerging [61,62]

Table 2. *Cont.*

Operational Domain	Existing Utility Practice	What EI Adds	Evidence Maturity
Live-line maintenance	Insulated bucket trucks; teleoperation; semi-automated manipulators	Task-level reasoning; shared autonomy; adaptive manipulation	Platforms exist; high-autonomy evidence mostly from broader robotics [63,64]
Emergency response	Human crews; remote-camera drones; rule-based inspection	Air-ground collaboration; dynamic hazard reasoning; limited physical intervention	Strong robotics evidence [65]; grid-specific deployment still early

3.1. Intelligent Inspection: Autonomous Perception in Unstructured Environments

Table 3 compares representative system configurations rather than fixed or mutually exclusive robot classes. Conventional inspection platforms may incorporate online replanning, active vision, or open-vocabulary models, while an EI-oriented platform does not inherently guarantee these functions. The comparison therefore focuses on how navigation, perception, and recognition capabilities are integrated and validated in a specified system, not on categorical superiority [66]. Many deployed inspection robots in substations and along transmission lines continue to use waypoint-based navigation and preconfigured perception pipelines. Such configurations can be disrupted by unmodeled obstacles, terrain changes, or degraded localization, although advanced conventional systems may also incorporate online replanning and active perception. EI research aims to mitigate these limitations through adaptive locomotion, semantic mapping, and perception-aware navigation, but universal all-terrain autonomy has not been demonstrated in grid environments. Focusing on specific carriers, quadruped robots in substations and UAVs along transmission corridors are now being equipped with terrain-aware locomotion and flight algorithms. At the enabling-technology level, general robotics studies have shown that embodied performance depends on the coupling of adaptive control, learning-based motion planning, and perception-aware navigation. Ref. [67] provides a general conceptual foundation for embodied AI by emphasizing the integration of learning-based methods with cognitive architectures in physically grounded environments. In this review, it is cited as a general theoretical enabler rather than as direct evidence of power-grid EI deployment. Regarding motion control, ref. [68] explicitly states that “the synergy of reinforcement learning and Model Predictive Control (ML-MPC) serves as a fundamental pillar for mobile robots to achieve continuous evolution through environmental interaction,” facilitating robust Sim2Real transfer in unstructured scenarios. For collaborative industrial tasks, ref. [69] proposed a bionic controller integrating vision-based perception and autonomous planning to address small-batch customized manufacturing. These works are not treated here as direct EI deployments in power grids, but as transferable technical foundations relevant to future utility inspection platforms.

Beyond mere navigation, the true advantage of the embodied paradigm lies in its capacity for active perception and pose adjustment. As illustrated in Figure 3, embodied carriers function as active agents that dynamically alter their physical state to optimize sensory input, contrasting sharply with the passive data collection of traditional drones. Specifically, a UAV can dynamically adjust its flight path, altitude, and gimbal angle to bypass an insulator string and clearly visualize a defect on the rear side [70]. Similarly, a quadruped robot may plan a crouching or leaning motion to inspect a hidden transformer oil valve. In ref. [71], an integrated perception–navigation–control framework was proposed to solve the problem of autonomous grounding clamp removal in live substations. By leveraging vision–language multimodal reasoning and Lyapunov-regularized

meta-learning, this embodied agent can interpret high-level maintenance commands and maintain strict physical stability while manipulating hardware in unmodeled power environments. Furthermore, ref. [72] explicitly states that “the synergy of hybrid UGV-UAV systems in GPS-denied subterranean environments enables robust exploration where traditional mapping and communication are unavailable.” This multi-agent coordination is relevant to underground cable trenches and power tunnels. It allows heterogeneous platforms to navigate unpredictable terrain collaboratively and may improve operational resilience during emergency response.

Table 3. Configuration-dependent qualitative comparison of representative inspection-system capabilities. Entries describe typical or emerging implementations rather than inherent properties of a robot class.

Capability Dimension	Human Inspector	Typical Deployed Inspection Configuration	Emerging EI-Oriented Configuration
Navigation and Mobility	Highly adaptable across varied terrains; relies on judgment and physical dexterity.	Often waypoint- or map-based; adaptability depends on the installed localization, online replanning, and obstacle-handling functions.	May integrate learning- or semantics-assisted navigation; performance remains platform-, environment-, and validation-dependent.
Perception Strategy	Active; dynamically adjusts viewing angles to overcome occlusions.	Often uses predefined viewpoints, although advanced conventional systems may incorporate active vision or online viewpoint replanning.	May integrate active perception or Next-Best-View planning; benefits depend on sensing, planning, control, and field validation.
Defect Recognition	Semantic understanding; capable of identifying novel, unseen anomalies based on experience.	Typically uses closed-set detection for predefined defect classes; some recent configurations can incorporate open-vocabulary models.	Potential open-vocabulary detection and task-conditioned reasoning; validated zero-shot fault diagnosis and safety-critical confirmation remain unavailable.

These terms should not be treated as interchangeable. Open-vocabulary object detection identifies object categories specified through language rather than a fixed training label set. Zero-shot anomaly recognition flags observations that deviate from learned normal conditions or a closed-set taxonomy without anomaly-specific training examples. Zero-shot fault diagnosis goes further by assigning a fault interpretation without task-specific examples, whereas safety-critical fault confirmation requires domain-specific validation, calibrated uncertainty, and independent or human verification before operational action. The literature reviewed here mainly supports research in open-vocabulary perception and anomaly recognition; it does not establish validated zero-shot fault diagnosis or autonomous safety-critical confirmation on weathered power-system assets.

3.2. Live-Line Maintenance: Dexterous Manipulation and Human–Robot Collaboration in High-Risk Scenarios

Live-line maintenance represents one of the most hazardous operations within the power sector, requiring precise physical interventions on energized high-voltage equipment. The application of Embodied Intelligence in this domain aims to transition from human high-risk exposure to robotic execution, relying heavily on complex physical interventions

via specialized mounted manipulators. Existing utility practice already includes insulated bucket trucks, manually operated tools, teleoperation, and limited semi-automated maintenance devices. What EI adds beyond these existing technologies is the integration of task-level semantic reasoning, adaptive shared autonomy, and continuous perception-action feedback under uncertain field conditions. However, the maturity of this transition remains uneven: stable mechanical platforms and teleoperation are already established, whereas highly autonomous manipulation in energized environments is still largely emerging. The primary realistic carriers for these tasks are vehicle-mounted dual-arm robots (integrated into insulated bucket trucks) and emerging aerial manipulation drones. These platforms execute intricate operations such as switching high-voltage disconnectors, stripping insulation from live wires, and crimping conductors. In ref. [73], the limitations of traditional power industrial control systems are highlighted, emphasizing the urgent need for advanced, automated architectures to manage the high uncertainty and dynamic complexity of modern power grids. Ref. [74] addresses the lack of automated actuators by proposing embodied intelligence (EI) technologies, such as VLA models, to reduce direct human exposure in high-risk power tasks like substation inspections and live-line work. Similarly, ref. [75] broadens the concept by treating micro-integrated energy systems as embodied intelligent agents, proposing a framework for autonomous monitoring, emergency fault handling, and self-maintenance in extreme environments with reduced on-site human intervention. Furthermore, ref. [76] systematically explores the deployment of embodied intelligent devices, including quadruped robots, wheeled robots, and UAVs, to execute autonomous safety operations and maintenance in large-scale energy storage stations, significantly reducing personnel risks and enhancing fault-handling efficiency. However, the physical execution of these tasks is fraught with mechanical limitations. Aerial manipulators, while offering unparalleled reach, suffer from severe under-actuation and are highly susceptible to aerodynamic disturbances. The reactive forces generated when an aerial robotic arm physically interacts with a stiff power line can easily destabilize the drone. Vehicle-mounted arms provide a stable base, but their workspace is constrained by boom reach and the arrangement of overhead conductors. These constraints can prevent the end effector from reaching a target without approaching surrounding energized components. Therefore, training a robotic arm to perform dangerous live-line tasks directly in the real world is unsafe and impractical due to the extreme risk of damaging critical grid assets. To overcome the immense difficulty of programming these complex manipulation skills, the field is increasingly relying on Sim-to-Real (simulation-to-reality) transfer learning [77,78]. In the context of live-line power-grid maintenance, however, the supporting evidence is still relatively limited and remains largely concentrated in controlled prototypes and transferable robotics studies, rather than mature large-scale utility deployment. These specific mechanical arms learn complex manipulation policies in high-fidelity physics-based simulators and seek to transfer the acquired capabilities to controlled real-world grid environments.

Given the current limitations of autonomous manipulation and the very low tolerance for error in live-line maintenance, teleoperation and shared autonomy serve as the critical safety net. In practical utility settings, shared autonomy currently appears more realistic than fully autonomous live-line intervention, as it allows the system to assist with perception, trajectory generation, and local control while preserving human supervisory authority in uncertain or safety-critical situations. The industry is transitioning from strict direct teleoperation, where human operators manually control every joint via complex joysticks, to an EI-driven “shared autonomy” paradigm. In this advanced framework, the autonomous “Brain” handles routine, low-level tasks such as trajectory planning and initial grasping based on visual servoing. The human operator is elevated to the role of a

high-level supervisor, taking over direct control via teleoperation only when the system encounters edge cases that exceed its cognitive confidence [79,80].

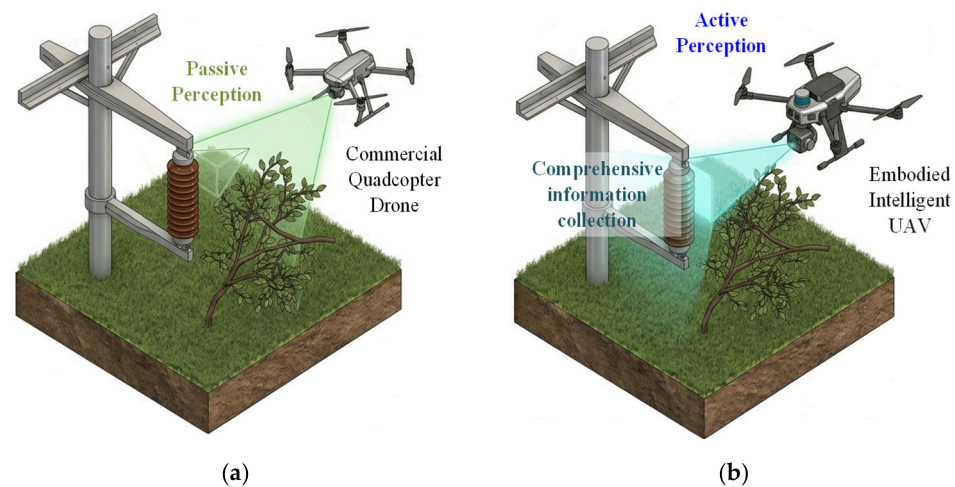


Figure 3. Conceptual comparison of predefined passive data collection and active viewpoint adaptation. The schematic illustrates information-acquisition logic only and does not provide a quantitative performance comparison. (a) Predefined Passive Data Collection. (b) Active Viewpoint Adaptation.

3.3. Emergency Response: Rapid Intervention and Environmental Interaction in Extreme Disasters

In the aftermath of extreme natural disasters such as earthquakes or typhoons, power grid infrastructure is often left in a state of catastrophic ruin. The application of Embodied Intelligence in emergency response focuses on rapid intervention and direct environmental interaction, transitioning robotic systems from mere observational tools to active rescue agents [5,81]. Table 4 contrasts the capabilities of traditional emergency response methods with those enabled by heterogeneous embodied swarms. At present, much of the strongest evidence for heterogeneous swarm coordination, risk-bounded navigation, and post-disaster physical intervention still comes from the broader disaster-robotics literature rather than from fully validated power-grid deployments. Therefore, the capabilities reviewed below should be interpreted as near-term transferable enablers with strong utility relevance, rather than as already mature, large-scale embodied deployments in grid emergency response.

Table 4. Conceptual comparison of emergency response paradigms in power systems [82].

Capability Dimension	Human Emergency Crews	Traditional Drones (Remote Cameras)	Heterogeneous Embodied Swarms (UAVs + Ground Robots)
Environmental Access	Severely restricted by debris, blocked roads, and secondary hazard risks.	Excellent aerial access, but incapable of physical interaction or ground-level sub-canopy inspection.	Synergistic access; UAVs provide macroscopic mapping, while ground robots traverse rubble for microscopic inspection.
Hazard Identification	High accuracy, but exposes personnel to lethal risks (e.g., hidden live wires).	Relies on human operators reviewing video feeds; prone to missing obscured hazards.	Potential automated risk assessment using multimodal sensing; field reliability remains to be validated.
Physical Intervention	High physical capability (clearing debris, repairing lines) but slow deployment.	Generally limited to observation, with little or no physical intervention.	May support emergency logistics and limited debris clearance under suitable conditions and supervision.

The first critical capability in this domain is navigating highly unstructured post-disaster environments. When traditional infrastructure collapses, pre-existing 3D maps

become obsolete, and GPS signals are frequently degraded. To address this, embodied systems employ heterogeneous swarms—combining high-altitude UAVs for rapid aerial mapping with rugged tracked or quadruped robots for ground-level traversal through debris. Ref. [83] proposed a lightweight air–ground cooperative mapping method for ground-robot navigation. UAV-derived 3D reconstructions were used to build a macroscopic 2D topological map that guides global planning. Ref. [84] introduced topology-aware UAV path-planning for rapid 3D reconstruction. The resulting structural information can support ground-robot planning in large-scale emergency scenarios.

In summary, to facilitate comparison across the heterogeneous evidence base, Table 5 summarizes representative studies by application setting, platform, methodological contribution, evidence role, and validation scope. It is worth mentioning that the selection is illustrative, and evidence roles may overlap, as defined in Section 1.2.

Table 5. Concise comparative summary of representative studies discussed in this review.

Study	Scenario/Platform	Core Contribution	Evidence Role	Validation Scope or Limitation
[30]	Inspection; quadruped	Hierarchical motion planning using kinodynamic search and B-spline optimization	Transferable enabler/utility-relevant precursor	Method-specific evidence; no common power-grid benchmark
[55,56]	Cross-domain manipulation; VLA agent	Multimodal instruction-to-action generation and dual-memory VLA	Transferable general robotics enabler	Grid-specific validation and safety assurance remain limited
[63,64]	Transmission-line operations; LineScout	Validated robotic platform for power-line field operations	Direct power-grid evidence and autonomous precursor	Does not implement the complete EI closed loop used in this review
[71]	Live-substation manipulation; mobile manipulator	Integrated perception-navigation-control with multimodal reasoning and Lyapunov-regularized control	Grid-oriented evidence and transferable control methodology	Task-specific grounding-clamp demonstration; broader comparison is unavailable
[72]	Underground inspection; hybrid UGV-UAV	Coordinated exploration in GPS-denied environments	Transferable general robotics enabler	Not a direct utility-field validation of a complete EI system
[76]	Energy-storage O&M; ground robots and UAVs	Heterogeneous embodied devices for autonomous safety operations and maintenance	Utility-relevant autonomous-operation study	Application-specific evidence; standardized cross-platform evaluation and large-scale field validation remain limited
[83,84]	Emergency mapping; UAV-ground robot team	Air-ground mapping and topology-aware path planning	Transferable emergency-response enabler	Focuses on mapping and navigation rather than physical intervention

In disaster settings, an embodied system would need to distinguish ordinary debris from hazards such as a downed energized conductor and compute a risk-bounded route under perception and localization uncertainty. The cited planning and control studies [85–87] provide transferable methods for uncertainty-aware navigation, but they do not by themselves demonstrate validated autonomous rescue in power-grid disasters. A longer-term objective is to support limited physical assistance and emergency logistics, such as clearing light debris under supervision or delivering communication relays and grounding equipment to isolated crews. These examples should be interpreted as bounded assistance scenarios rather than evidence that autonomous physical rescue is currently mature [88].

4. Comprehensive Benefits, Challenges, and Future Outlook

While Section 3 demonstrated the disruptive potential of EI across specific field operations, transitioning from isolated laboratory demonstrations to scaled engineering applications requires a macro-level evaluation. This section analyzes the socio-economic benefits, objectively assesses the current system-level bottlenecks that prevent immediate mass adoption, and outlines the future trajectory of EI in the power sector.

4.1. Comprehensive Benefits Analysis: Reshaping the Industry Ecosystem

EI may contribute to safer and more efficient power-system field operations, but the scale of the benefit depends on task design, reliability, regulation, and deployment maturity. A near-term benefit is the potential reduction in direct human exposure to selected high-risk activities through remote operation, shared autonomy, and supervised robotic assistance. This does not eliminate occupational hazards or justify the full replacement of field personnel; risks may shift toward supervision, maintenance, cybersecurity, and abnormal-event management. Similarly, mobile inspection systems may support more frequent monitoring and earlier fault identification, but reductions in outage duration, logistics cost, or workforce demand remain context-dependent and require field evidence [89–91].

Changes in workforce composition may accompany the adoption of robotic and AI-assisted field systems, particularly if routine high-risk tasks become increasingly automated while demand grows for supervision, fleet dispatch, software maintenance, and data-centric operational roles [92–96]. Figure 4 is an author-generated thought experiment based on three assumptions: progressive automation of selected routine tasks after 2030, broadly stable operational-service demand, and a shift toward supervisory and technical roles. These particular values were selected solely to make the assumed directional contrast visible. The sharper change between 2030 and 2040 represents a stylized acceleration phase after 2030; it is not tied to an adoption threshold estimated from the data. No functional relationship between automation penetration and employment demand is asserted, and no sensitivity analysis, confidence interval, or forecasting claim is intended. The figure is therefore non-evidentiary and is not used to support the technical conclusions of this review.

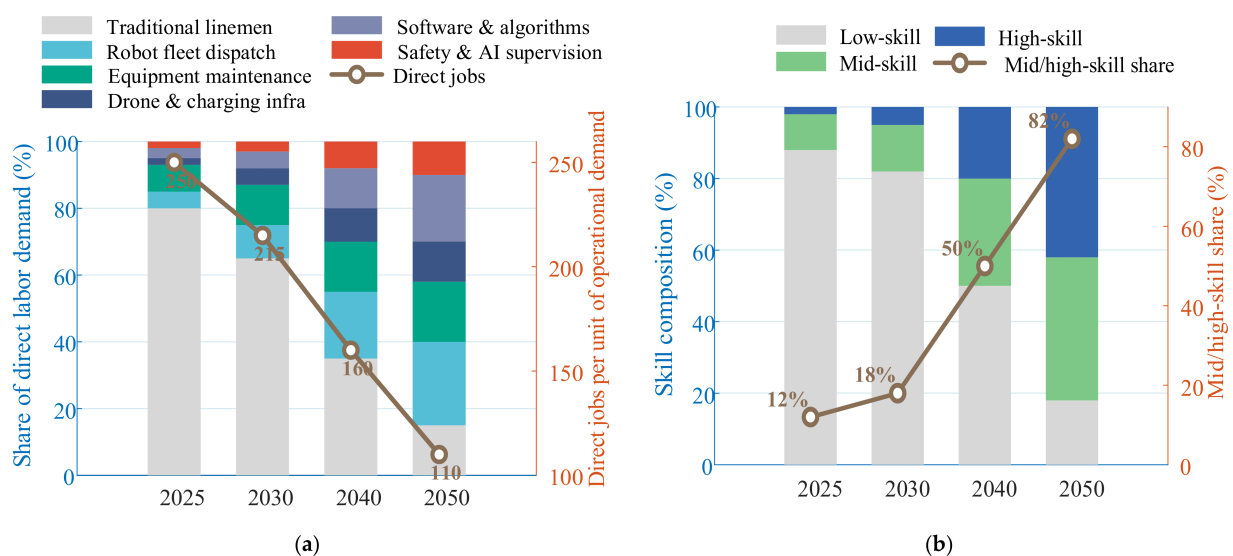


Figure 4. Author-generated, non-predictive thought experiment illustrating one possible directional shift in labor demand and skill composition under progressive EI adoption. The displayed values are arbitrary scenario inputs selected only to separate illustrative trajectories; they are not outputs of an empirical or mathematical model and are not used as evidence in this review. (a) Changes in job type structure. (b) Changes in the structure of job skill levels.

4.2. Current System-Level Challenges: Hardware, Software, and Socio-Economic Realities

Despite the compelling benefits, the widespread adoption of Embodied Intelligence in power systems is currently constrained by profound system-level bottlenecks. An objective analysis reveals that the physical and cognitive capabilities of current embodied agents often fall short of the stringent reliability requirements demanded by critical grid infrastructure. Firstly, hardware limitations in extreme environments present a formidable barrier. Power grids span diverse geographical regions, exposing robotic carriers to severe environmental stressors. Current battery technologies suffer from drastic capacity degradation in extreme cold, such as in high-altitude regions, severely limiting the operational endurance of UAVs and quadruped robots [97–99]. In real grid operations, this is not merely an efficiency issue: long transmission-corridor patrols, mountainous access routes, and post-disaster dispatch tasks require sufficient energy not only for mission execution but also for safe return, fallback landing, or contingency re-routing. Furthermore, the intense electromagnetic fields (EMF) generated by 500 kV and higher ultra-high-voltage (UHV) transmission lines pose a severe threat to the electromechanical reliability of the agents [100]. This challenge is tightly linked to grid reliability constraints, because tasks performed close to energized assets require stable localization and deterministic actuation within procedure-, voltage-, and task-specific clearance and positioning requirements. Beyond environmental endurance, the physical execution of tasks is fraught with mechanical limitations. As observed in disaster response scenarios, ground robots manipulating debris of unknown mass frequently experience actuator saturation or tipping. Similarly, aerial manipulators suffer from severe under-actuation; the reactive forces generated when a drone-mounted arm interacts with a stiff power line can easily destabilize the carrier. Ref. [101] explicitly states that executing precise airdrops or physical interventions in the turbulent wind fields of complex terrains remains aerodynamically unstable, as sudden payload releases can cause severe altitude drops or attitude oscillations. In power-grid settings, such instability is especially problematic because operational failure may occur in close proximity to energized conductors, damaged towers, or narrow access structures where safety margins are inherently limited.

Secondly, the software and cognitive architectures of EI systems face critical reliability thresholds, most notably the risks associated with Large Language Model (LLM) “hallucinations” and edge computing latency. In high-risk grid operations, very high reliability is required; even infrequent semantic errors can create safety-critical consequences [102,103]. If a Vision–Language Model incorrectly classifies a live, downed conductor as harmless debris due to visual degradation from dust or rain, the resulting path planning could lead to the immediate destruction of the robot or trigger secondary electrical faults. From an engineering standpoint, the key issue is that field operations in power systems are governed by highly standardized procedures, strict switching sequences, and fail-safe execution requirements; therefore, semantic errors in embodied agents can translate directly into mis-operation risk rather than merely degraded task performance. Latency requirements are layer- and task-dependent rather than governed by a single threshold. Joint-level servo, contact-stabilization, and protective-control loops require much faster local updates than semantic task planning or VLA inference. Safety-critical low-level loops should therefore remain onboard or at the edge and include independently verified fallback behavior. Slower perception aggregation and task-level reasoning may use edge–cloud resources when communication quality and supervisory constraints permit. Mobile platforms may nevertheless face computational trade-offs when dense mapping, trajectory replanning, and large-model inference run concurrently [104,105]. When a UAV performs aggressive maneuvers for active perception, rapid acceleration changes can cause severe drift in its visual–inertial odometry (VIO), and excessive end-to-end latency may delay

corrective state estimation or replanning. In real substations, narrow passages, staircases, handrails, dense equipment layouts, and energized apparatus all require low-latency local response rather than delayed cloud-side correction. Additionally, proposed Sim-to-Real transfer methods for complex manipulation face profound reality gaps. Highly deformable linear objects, such as multi-strand ACSR cables, exhibit complex, non-linear dynamic behaviors like hysteresis and variable bending stiffness that are notoriously difficult to model accurately [106,107]. This discrepancy often leads to policy degradation, where a robotic arm that performs flawlessly in a physics engine fails to properly grasp the actual cable, especially when unmodeled factors like freezing temperatures stiffen the cable insulation. These Sim-to-Real gaps become even more critical in utility environments because aged, weathered, corroded, or contaminated equipment often deviates substantially from idealized training assumptions. Regional differences in supporting digital infrastructure may further influence the feasibility of large-scale deployment [108].

Cybersecurity adds a distinct reliability risk for networked EI agents operating on critical grid infrastructure [109–114]. Conventional industrial-control threats include unauthorized access, spoofed telemetry, denial of service, communication disruption, and command tampering. AI-specific threats include adversarial sensor inputs, data poisoning, model backdoors, prompt or instruction manipulation, out-of-distribution inputs, and compromise of model-update pipelines. Within the perception–cognition–execution architecture, adversarial sensing and localization spoofing primarily affect perception; poisoning, backdoors, instruction manipulation, and distribution shift affect cognition; and command tampering or unsafe generated outputs affect execution and multi-agent coordination. Mitigation therefore requires both conventional defense-in-depth and AI-specific assurance: redundant sensing, authenticated and segmented communication, secure update pipelines, uncertainty and anomaly detection, constrained low-level control, predefined minimum-risk states, and fail-safe human override. Learned components should not directly command safety-critical actuators without an independently validated safety layer. Differences in regional digital infrastructure can also constrain the supporting communication and computing capacity needed for deployment [115,116].

Based on this, Figure 5 uses the 2025 cross-section of a province-year text dataset covering 31 provincial-level regions from 2002 to 2025. The government work reports were processed using word segmentation. For province i , F_i is the unweighted sum of occurrences of 51 predefined terms related to digital infrastructure, and T_i is the total report word count. The descriptive indicator is $I_i = 100(F_i/T_i)$, expressed as a percentage; no additional term weighting is applied. This scaling is consistent with the underlying calculation file. The indicator measures the relative frequency of policy language in a specific document corpus. It is not an official statistic of installed infrastructure, investment, deployment outcomes, or readiness for EI in power-grid operations. It has not been independently validated against physical infrastructure measures, and uncertainty arises from dictionary selection, report length and writing style, corpus preparation, and year-specific policy language; consequently, no confidence interval or causal interpretation is claimed. The 2025 map is retained only to illustrate cross-regional heterogeneity in policy attention, not to rank provinces by technological capability or to infer that policy attention causes EI deployment.

Finally, another important limitation is the current lack of standardized evaluation benchmarks for embodied field operations in power systems [117,118]. Existing studies often report performance through task-specific indicators, such as recognition accuracy, planning efficiency, task completion rate, or stability-related measures, but these results are typically obtained under different datasets, hardware platforms, simulation assumptions, and field conditions. As a result, the current literature remains informative but is not yet directly comparable in a strict benchmarking sense. Future research should therefore

move beyond isolated proof-of-concept demonstrations and develop unified evaluation tasks, benchmark datasets, and field-relevant validation protocols for inspection, live-line manipulation, and post-disaster response in utility environments.

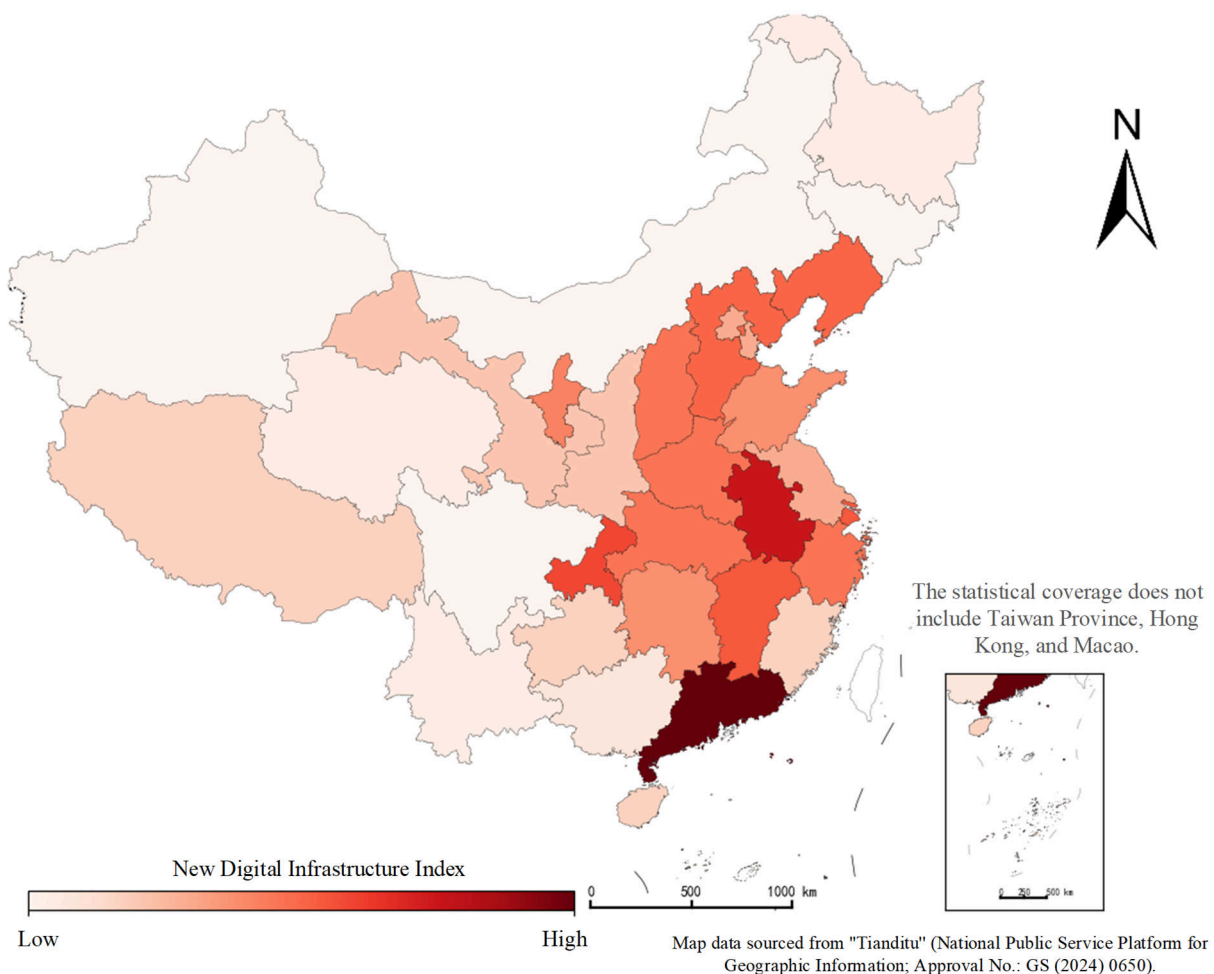


Figure 5. Author-generated descriptive map of the 2025 provincial text-frequency proxy for policy attention to new digital infrastructure in mainland China. The proxy uses an unweighted 51-term dictionary applied to provincial government work reports and should not be interpreted as installed capacity, investment, or readiness for power-grid EI [108].

4.3. Future Directions: Toward More Autonomous and Reliably Supervised Grid Operations

To overcome these bottlenecks and advance the potential applications of Embodied Intelligence, future research and industrial development should focus on highly specialized, collaborative, and standardized ecosystems. The transition from general-purpose AI to domain-specific architectures is paramount.

The foremost direction is the development of domain-specific “Power Grid Embodied Foundation Models.” General-purpose VLMs lack the rigorous domain knowledge required for critical infrastructure. Future embodied “brains” should incorporate power grid physical laws, topological constraints, and stringent safety regulations. In ref. [119], a domain-specific taxonomy and benchmarking framework for LLMs was proposed to address the lack of specialized evaluation standards in industrial disciplines. This work provides a foundational metric for integrating complex regulatory compliance, such as IEEE and IEC standards, into the reasoning processes of AI agents. In ref. [120], the application of LLMs in electrochemical energy storage was explored to solve challenges in material discovery and real-time safety diagnostics. By synthesizing multi-source data and generating

optimization strategies, this approach ensures that the operational parameters of energy systems remain within physically safe boundaries, mirroring the requirement for strict adherence to industry operating procedures. Furthermore, ref. [121] introduced an intelligent three-layer architecture designed to exploit edge data in modern power systems through LLM-based multimodal fusion and closed-loop control. This framework specifically targets high-stakes scenarios such as intelligent substation inspection and virtual power plant dispatch, demonstrating how LLMs can unlock the value of heterogeneous data while maintaining system resilience. Collectively, these studies underscore that the convergence of domain-specific benchmarks, physical constraint modeling, and edge-deployed intelligence is essential for ensuring that autonomous agents in power systems are both semantically logical and physically secure.

Simultaneously, the operational paradigm may evolve from single-agent tasks to heterogeneous air-ground swarm collaboration. In ref. [122], an RL framework for drone fleet management was proposed to solve the problem of maintaining persistent connectivity in Industrial Internet of Things environments. By dynamically optimizing drone deployment in response to fluctuating bandwidth demands and wind energy availability, the system ensures a self-sustaining communication backbone with reduced human intervention. In ref. [123], an integrated autonomous drone system was developed to address the inefficiencies and human errors inherent in manual power grid monitoring. This approach merges AI-based real-time fault detection with energy harvesting and advanced navigational algorithms, enabling reliable inspection missions even in harsh weather conditions up to 30 knots. In the context of this review, this study is cited as a utility-relevant autonomous precursor demonstrating persistent inspection infrastructure, rather than as a full EI implementation under the stricter perception–cognition–execution criterion adopted in Section 2.1. Future EI deployments may build on these cooperative air–ground operations. UAVs could reduce ground-level occlusions by providing global path planning and 3D semantic maps from the air. Rugged ground robots and vehicle-mounted arms could then use this guidance to navigate blind spots and execute supervised physical interventions. This synergistic approach effectively compensates for the kinematic and payload limitations of individual carriers.

Advancing beyond prototypes will require scenario-specific certification and runtime-assurance frameworks [124]. Safety-critical control logic should be formally verified where feasible, while learned planning or perception modules should operate behind independently validated safety constraints, control-barrier or equivalent protective layers, and bounded low-level controllers. Runtime monitoring should combine uncertainty estimation, out-of-distribution detection, redundant sensing and communication, and explicit transition to a predefined minimum-risk state when confidence, connectivity, or control margins are inadequate. Human supervisors must retain clearly defined authority to approve, interrupt, or assume control of high-consequence actions. Certification evidence should therefore specify the operating domain, fallback behavior, human–system authority allocation, and field-validation conditions rather than treating autonomy as a single system-wide label.

5. Conclusions

This review systematically explored the transformative potential of EI within the field operations of modern power systems. Ultimately, EI is not merely an incremental upgrade to traditional industrial robotics; rather, it is a promising enabling force that may progressively reshape the operational paradigm of the power grid. By transitioning from human-centric, high-risk interventions to increasingly autonomous and intelligent robotic executions, EI represents a promising long-term pathway toward “intrinsic safety” and

substantially safer industry practice. Based on a comprehensive analysis of conceptual architectures, core application scenarios, and system-level challenges, the main conclusions and future recommendations of this paper are summarized as follows:

(1) The Necessity of the “Brain–Body” Architectural Shift: The fundamental limitation of traditional grid automation is the decoupling of perception and action. The future of grid operations relies on the “Perception–Cognition–Execution” closed loop. Integrating versatile physical carriers, such as quadrupedal robots and aerial manipulators, with advanced cognitive “brains” is essential for enabling autonomous navigation and semantic reasoning in highly unstructured and dynamic grid environments.

(2) Progression from Passive Observation toward Supervised Physical Assistance: EI-related methods may extend grid inspection through active perception and open-vocabulary object detection and zero-shot anomaly detection, although reliable zero-shot performance on utility assets remains an emerging research topic. In live-line maintenance, Sim-to-Real methods and shared autonomy may reduce direct human exposure while preserving supervisory control. In emergency response, air–ground systems can support mapping, risk-aware navigation, communication relay, and limited logistics; mature autonomous physical rescue in power-grid disasters has not yet been demonstrated.

(3) Addressing Socio-Economic Imbalances through Strategic Policy: While EI significantly enhances labor productivity and aligns with the demographic shift toward a technology-intensive workforce, its widespread adoption is currently hindered by high initial deployment costs and regional disparities. To reduce the risk of widening technological gaps, it is recommended that future national policies and industry frameworks provide targeted funding, phased deployment strategies, and cross-regional technology transfers to support resource-constrained regions, ensuring an equitable modernization of the entire grid network.

(4) The Imperative of Deep Interdisciplinary Integration: Overcoming the remaining system-level bottlenecks, such as battery degradation in extreme climates, electromagnetic interference, the reality gap in dexterous manipulation, and the safety-critical risk of large-model “hallucinations”, cannot be achieved within a single technological silo. The realization of more autonomous and reliably supervised grid operations requires the deep, cross-disciplinary convergence of power system engineering, artificial intelligence, robotics, and advanced materials science. Only through this holistic integration can the industry develop the domain-specific embodied foundation models and ultra-reliable physical carriers required for critical infrastructure.

While many of the advanced embodied capabilities reviewed in this paper remain at the stage of laboratory validation, prototype demonstration, or early transfer from broader robotics, translating them into dependable utility practice requires bridging the gap to real-world deployment. Moving forward, this transition will require field-validated evidence and standardized benchmarks in real power-grid environments. It will also require deeper formal analysis of control safety and robust cybersecurity assurance for networked embodied agents.

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Abbreviations

The following abbreviations are used in this manuscript:

ACSR	Aluminum Conductors Steel-Reinforced
AI	Artificial Intelligence
EI	Embodied Intelligence
EMF	Electromagnetic Fields
EMI	Electromagnetic Interference
LLM	Large Language Model
MPC	Model Predictive Control
UAV	Unmanned Aerial Vehicle
VIO	Visual-Inertial Odometry
VLA	Vision-Language-Action
VLM	Vision-Language Model

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