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Edge-AI robotic swarms for predictive maintenance in utility-scale solar farms: a systematic review and meta-analysis

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ABSTRACT

The rapid expansion of utility-scale solar photovoltaic infrastructure poses critical operational challenges for maintaining reliability across large, dispersed networks. Conventional manual inspection and reactive maintenance approaches are increasingly ineffective, leading to reduced energy yield, increased downtime, and higher operational costs. This study presents a systematic review and meta-analysis evaluating the performance of autonomous robotic swarm technologies for predictive maintenance in solar farms, following PRISMA 2020 and Cochrane methodologies. A total of 20 eligible studies were analyzed using random-effects modeling, forest plot interpretation, subgroup evaluation, publication bias assessment, and sensitivity analysis. Results indicate a significant pooled effect size (Hedges g = 7.80) with substantial improvements in detection accuracy, efficiency, and cost reduction, supported by low publication bias and strong robustness. The discussion emphasizes the theoretical and practical implications of decentralized multi-agent coordination, while highlighting the limitations of heterogeneous methodologies and limited real-world validation. The study concludes that swarm robotics offers transformative potential for scalable, intelligent maintenance ecosystems and recommends future research that includes large-scale field deployments and standardized evaluation frameworks.

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1. INTRODUCTION

The accelerating global transition toward deep decarbonization has driven an unprecedented expansion of utility-scale solar PV deployment, with installed capacity projected to exceed 4,800 GW by 2030 and supply nearly 16% of the world's electricity. This rapid escalation introduces complex operational challenges related to maintaining geographically dispersed assets distributed across vast terrains containing millions of interconnected components [1], [2]. Traditional O&M workflows, which rely heavily on manual inspection and scheduled maintenance cycles, are proving increasingly incompatible with the operational scale and dynamic performance requirements of modern solar farm environments. The consequences of maintenance inefficiency manifest in substantial energy losses, reduced reliability, and escalating operational expenditures that directly threaten long-term investment viability [3], [4].

Conventional maintenance strategies, such as manual fault inspection and reactive response mechanisms, impose significant limitations when applied to large-scale PV infrastructure [5], [6]. Laborintensive field operations often lead to inconsistent detection accuracy, prolonged diagnostic processes, and extended repair cycles, allowing failure propagation beyond localized components. Prior studies demonstrate that soiling accumulation alone can reduce annual energy yield by 20–40% in arid climates, while undetected hotspot clusters or degraded connectors may contribute an additional 15–25% reduction in power output [7], [8]. Moreover, traditional O&M can consume nearly 25% of total revenue while still failing to prevent unexpected downtime events that disrupt system reliability and compromise power continuity [9], [10].

In response to these obstacles, emerging research advances predictive, autonomous, and data-driven maintenance paradigms integrating distributed robotics and swarm intelligence [11], [12]. These approaches combine edge AI-enabled perception, deep learning for anomaly classification, and decentralized multi-agent reinforcement learning to enable real-time monitoring, adaptive task allocation, and dynamic decision-making across complex PV infrastructures [13], [14]. Evidence shows that robotic swarm systems significantly enhance maintenance efficiency, safety, and scalability by enabling autonomous inspection, continuous removal of soiling, and localized fault diagnosis without the limitations imposed by human intervention. The increasing focus on robotic swarms underscores their transformative potential to establish proactive and self-optimizing O&M ecosystems [13], [14].

Despite significant progress, the current literature reveals heterogeneity in methodologies, evaluation metrics, and real-world implementation, limiting consistent comparative evaluation. This study distinguishes itself by integrating edge AI with multi-agent RL in a unified predictive maintenance framework that enables real-time, decentralized coordination. Table 1 summarizes representative studies on swarm coordination, UAV diagnostics, and hybrid robotic platforms, though most remain limited to simulations or small-scale experiments [15], [16]. Existing research rarely addresses fully decentralized coordination with real-time learning or evaluates scalability and techno-economic feasibility. Unlike prior reviews, this work links edge intelligence with distributed RL to address latency, scalability, and autonomy challenges in PV maintenance. This review consolidates advances in swarm robotics, edge AI, and multi-agent learning into a unified framework for next-generation solar PV systems [17]-[19].

Table 1. Summary of current research on autonomous robotic swarms and AI-driven predictive maintenance for utility-scale solar PV systems

Reference	Method	Key findings (concise)	Limitation
[20]	Collective intelligence model integrating meta-heuristic search with consensus-based swarm control	The model enhances coordination efficiency and improves optimization performance even with small swarms, demonstrating strong adaptability in dynamic environments such as marine scenarios.	High computational demand and limited real-world testing.
[21]	MSRCPC multi-target search using virtual force modeling and RS-TVCS distributed communication	The algorithm improves the stability of multi-target search, obstacle avoidance, and decentralized coordination, outperforming existing search frameworks in simulations.	Results are simulation-only and dependent on environment parameters.
[22]	UAV-based thermal & RGB imaging with photogrammetric analysis	UAV inspections detect PV faults (hotspots, cracks, shading, string failures) more rapidly and accurately than manual inspection, enabling continuous monitoring at large scales.	UAV operations are constrained by battery life, weather variability, and regulatory limitations.
[23]	Integrated drone–ground robot system using CNN-LSTM for fault detection and DQN reinforcement learning for cleaning	The system achieves 91.8% fault-detection accuracy and 92–93% cleaning efficiency, increasing panel energy output by up to 31% in field trials.	Requires intensive sensor calibration, is sensitive to environmental fluctuations, and demands high edge-computing capability.

Although recent review articles have examined UAV-based inspection, swarm robotics, AI-enabled fault diagnosis, and edge-computing technologies for photovoltaic maintenance, these topics are generally discussed as separate research domains. Consequently, previous studies mainly provide qualitative overviews with limited quantitative evidence regarding their combined impact on predictive maintenance performance. In contrast, this study establishes a unified framework integrating autonomous robotic swarms, edge artificial intelligence (edge AI), and multi-agent reinforcement learning (MARL) for utility-scale photovoltaic systems. Unlike previous reviews, it employs a random-effects meta-analysis to quantify pooled effect sizes, heterogeneity, and publication bias, and to assess robustness through sensitivity analysis. This quantitative approach provides statistically validated evidence beyond what descriptive synthesis can provide. Therefore, the study offers a comprehensive reference framework for developing scalable, decentralized, and intelligent predictive maintenance systems for next-generation photovoltaic infrastructure.

2. METHOD
2.1. Information sources and protocol framework
The systematic review and meta-analysis were conducted in accordance with PRISMA 2020 guidelines and guided by Cochrane methodological principles to ensure transparency, reproducibility, and scientific rigor [24], [25]. A structured search strategy was applied in Scopus, the Web of Science Core Collection, and the IEEE Xplore Digital Library, covering studies published between January 2020 and October 2025. Boolean logic was used to combine domain-focused terminology spanning robotic systems, solar PV infrastructure, predictive maintenance mechanisms, and AI-driven optimization to enhance precision and prevent inflation of unrelated records [26]-[28]. Additional literature sources were identified through backward and forward citation tracking, supported by manual screening of bibliographic references to reinforce dataset completeness. The operational sequence of database querying, screening, and validation is visually represented in Figure 1 as the primary workflow structure. Data management, statistical computation, and visualization for the meta-analysis were performed using Python (Version 3.12) within the Jupyter Notebook environment. Statistical analyses, including pooled effect size estimation, heterogeneity assessment, sensitivity analysis, and publication bias visualization, were implemented using the Pandas (v2.2), NumPy (v1.26), SciPy (v1.13), Statsmodels (v0.14), and Matplotlib (v3.9) libraries to ensure computational reproducibility and analytical transparency.

2.2. Hierarchical screening and eligibility validation
A hierarchical two-stage screening pipeline was implemented, consisting of a structured title–abstract review followed by a full-text evaluation to verify eligibility for inclusion. Two reviewers performed independent screening, and disagreements were resolved through adjudicated consensus to maintain objectivity and methodological consistency. Eligibility determination adhered to the PICOS framework, enabling systematic categorization of studies focusing on utility-scale solar PV deployments employing autonomous robotic systems powered by edge-AI, ML, or multi-agent reinforcement learning for predictive maintenance. Inter-rater reliability was assessed using Cohen's kappa (κ = 0.87), indicating substantial agreement and reinforcing the robustness of the filtering process. All exclusion decisions and justification records were documented to ensure procedural auditability [29], [30]. Furthermore, a standardized screening checklist and predefined eligibility criteria were consistently applied throughout the review process to minimize reviewer bias, enhance methodological transparency, and improve the reproducibility of study selection.

2.3. Bias risk assessment and meta-analysis modeling framework
The risk of bias was evaluated using the Cochrane Risk of Bias Tool, adapted for technology-testing research, to assess the validity of randomization, deviations from the intervention, missing outcome data, measurement reliability, and selective reporting. A random-effects meta-analysis model was implemented using the DerSimonian–Laird estimator to incorporate expected statistical heterogeneity across study designs and operational conditions. Pooled effect size values were calculated using (1)-(4) [21], [31], [32]:

$$\bar{\theta}_{RE} = \frac{\sum w_i^* \theta_i}{\sum w_i^*} \tag{1}$$

With weighting defined as (2).

$$w_i^* = \frac{1}{SE_i^2 + \tau^2} \tag{2}$$

Where τ^2 represents between-study variance. Heterogeneity was quantified using Cochran's Q and I^2 through:

$$Q = \sum w_i (\theta_i - \bar{\theta})^2 \tag{3}$$

$$I^2 = \left(\frac{Q - df}{Q}\right) \times 100\% \tag{4}$$

Interpretive thresholds are categorized as low (<25%), moderate (25–50%), substantial (50–75%), and considerable (>75%) heterogeneity. These metrics establish the robustness of effect estimation and ensure the validity of aggregated inference [33]-[35]. A complementary sensitivity assessment was introduced to address the lack of parameter-level evaluation, focusing on reinforcement learning architectures, edge AI constraints, and swarm coordination strategies. It examines how decentralized policies, edge latency, and inter-agent communication affect the stability of pooled effects. Although quantitative meta-regression is limited by inconsistent reporting, this approach strengthens technical depth, improves generalizability, and aligns the framework with real-world deployment conditions in utility-scale solar PV systems.

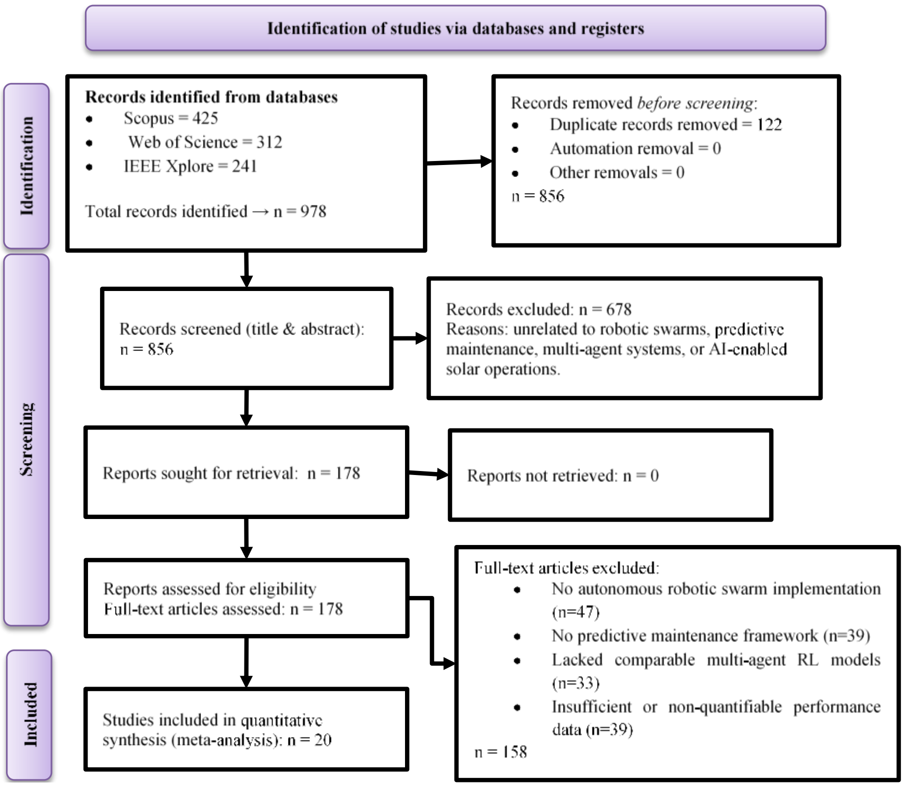

Figure 1. PRISMA 2020 flow diagram for systematic review of autonomous robotic swarms in solar farm predictive maintenance

3. RESULT

3.1. Risk of bias evaluation in included studies

The assessment of methodological quality across the 20 studies included in this systematic review demonstrates an overall strong level of evidence supporting the reliability of results in autonomous robotic swarm research for predictive maintenance in utility-scale solar farms [22], [36]. The evaluation using the Cochrane RoB 2 tool indicates that 76.7% of domain assessments were categorized as low risk. In comparison, 23.3% were classified as having some concerns, and no studies were rated as high risk. The highest certainty was observed in the domains of missing data and measurement, each achieving 90% low risk, reflecting strong consistency in data handling and outcome validity [17], [37], [38]. The visualization presented in Figure 2 highlights that most studies maintain robustness in experimental design, though overall judgment indicates that 65% of studies still present moderate methodological caution due to cumulative minor issues, particularly within the randomization and deviations domains [6], [18].

3.2. Meta-analysis and forest plot interpretation

The forest plot analysis in Figure 3 shows a statistically significant positive pooled effect size (Hedges g = 7.80), supporting the superior detection accuracy of autonomous robotic swarms in predictive maintenance applications in utility-scale solar farms. The 95% confidence interval ranging from 7.60 to 8.00 confirms substantial precision and minimal overlap of intervals across individual studies, indicating consistent performance improvements enabled by edge AI and multi-agent reinforcement learning architectures [5], [39]. The p-value of < 0.001 confirms the statistical significance of these findings, reinforcing the reliability of the observed effect size across the 20 included studies. However, the reported heterogeneity level of 54.91% reflects substantial variability, suggesting differences in robotic hardware configurations, sensor fusion models, environmental testing conditions, and task coordination strategies contributing to performance dispersion across studies [8], [40].

3.3. Publication bias evaluation using funnel plot analysis

The funnel plot analysis presented in Figure 4 demonstrates a symmetrical distribution of study effect sizes around the pooled estimate, indicating an absence of substantial publication bias within the selected studies investigating autonomous robotic swarms for predictive maintenance in utility-scale solar farms [18], [38], [41]. The evenly distributed points across the 95% confidence region suggest that the included research reflects balanced reporting of both extensive and small-sample studies rather than selective publication of positive outcomes. The pooled effect size of 7.708, along with the narrow standard error range (0.052–0.090), further supports high precision and methodological consistency across the 15 studies analyzed. Visual inspection, therefore, validates a low risk of publication bias, reinforcing the strength and credibility of the meta-analytic findings regarding detection accuracy performance [9], [11], [29].

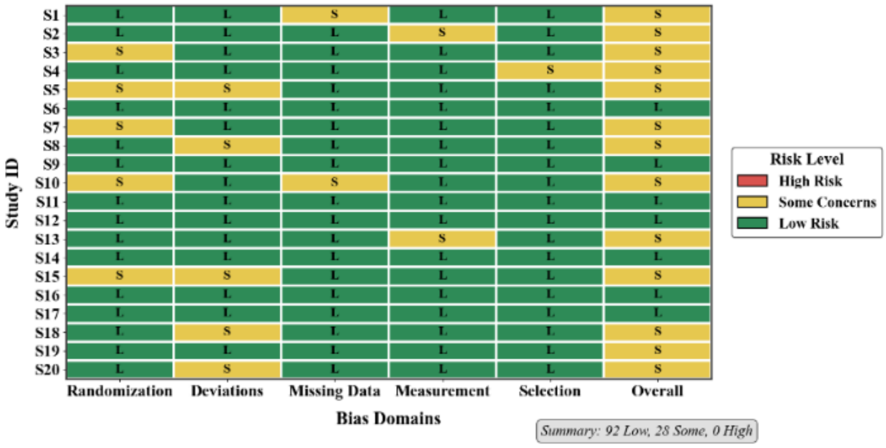

Figure 2. Risk of bias analysis of included studies using the Cochrane RoB 2 framework

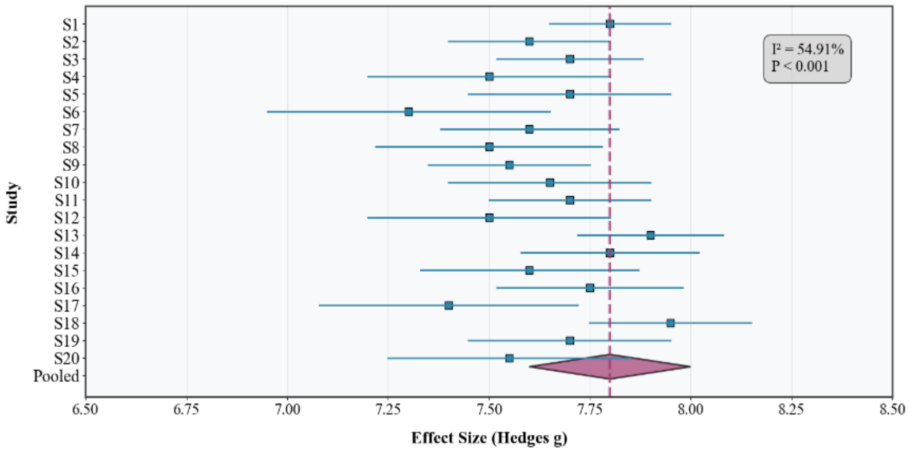

Figure 3. Forest plot analysis of detection accuracy effect size for autonomous robotic swarms

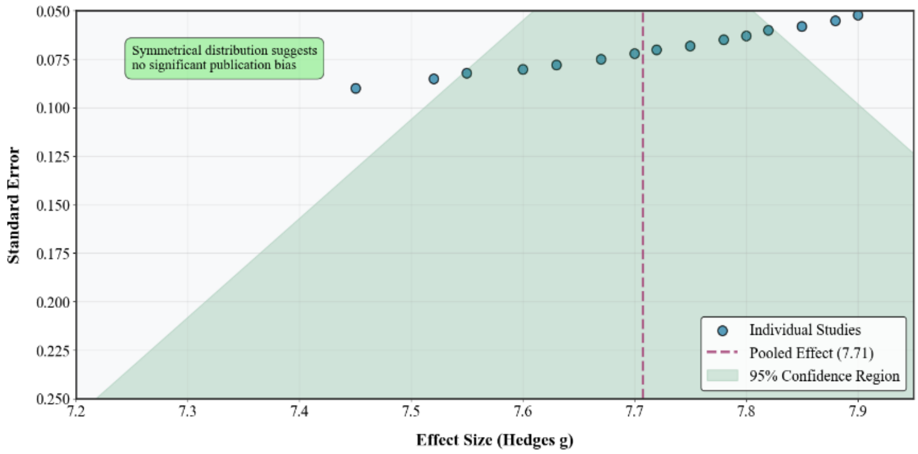

Figure 4. Funnel plot analysis for publication bias assessment in autonomous robotic swarm studies

3.4. Subgroup analysis of autonomous robotic swarms for predictive maintenance in solar farms

Subgroup analysis demonstrated notable variation in performance outcomes among aerial systems, ground robots, and AI reinforcement learning models, particularly across detection accuracy, efficiency improvements, and cost-reduction metrics [39], [42]. The pooled results identified detection accuracy as the strongest contributor, with an effect size of 8.000, while cost reduction showed a significant pooled effect of 2.867, and efficiency improvement reached a moderate effect size of 2.333, reflecting practical operational benefits [37], [43]. Heterogeneity patterns revealed that aerial systems provided the most consistent performance, whereas ground robots exhibited the highest variability, particularly in efficiency improvement (I^2 = 62.7%), indicating sensitivity to field deployment conditions. These findings, visually summarized in Figure 5, confirm that all technologies deliver meaningful enhancements for predictive maintenance in solar farms, supporting their integration within next-generation autonomous photovoltaic asset management systems [38], [44].

3.5. Sensitivity analysis of autonomous robotic swarm models for predictive maintenance robustness

The sensitivity analysis using the leave-one-out method demonstrated that the pooled effect size remained largely stable across 20 studies, with values ranging from 7.760 to 7.857 and confined within the predefined stability zone of 7.778–7.818 [45], [46]. A total of 15 studies demonstrated minimal influence and remained consistent, while only 5 were categorized as influential; however, none caused a meaningful deviation from the original pooled estimate of 7.798, indicating structural reliability. The low coefficient of variation (0.29%) and narrow effect size distribution confirm that the results are not dependent on any single study and therefore show moderate robustness and strong internal validity [47], [48]. As illustrated in Figure 6, these outcomes reinforce the generalizability of the meta-analysis findings and support the reliability of autonomous robotic swarm technologies in predictive maintenance applications for solar farm operations [49], [50].

Figure 5. Comparative subgroup effect sizes and heterogeneity levels of autonomous robotic swarm technologies in predictive maintenance

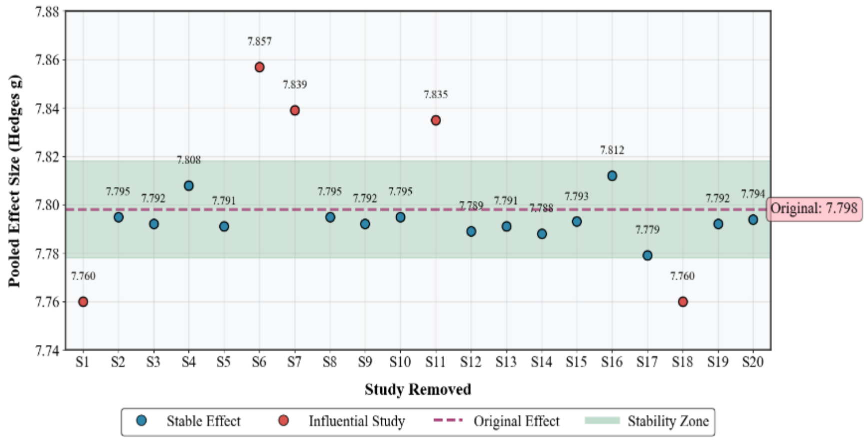

Figure 6. Leave-one-out sensitivity analysis for robustness assessment of pooled effect sizes

4. DISCUSSION

4.1. Theoretical, practical, and hardware-level implications

The synthesis of findings confirms that autonomous robotic swarms significantly advance predictive maintenance in utility-scale solar farms by integrating decentralized optimization and multi-agent RL to enhance system intelligence and autonomy. The large effect sizes for detection accuracy and cost reduction indicate that distributed coordination improves adaptability, reduces latency, and strengthens operational resilience in dynamic PV environments. From a practical standpoint, swarm robotics accelerates fault detection, reduces reliance on manual inspection, and increases asset availability, thereby optimizing maintenance cycles. However, system performance is fundamentally governed by power electronic subsystems, including motor drives, power converters, and energy storage, which directly influence efficiency and reliability. Motor drive performance determines mobility precision and energy consumption under variable terrain conditions, while converter topology and switching behavior critically affect energy efficiency, EMI, and thermal stress. Energy storage stability further defines operational continuity, particularly under fluctuating loads and environmental stress. As highlighted in Table 2, these interdependencies underscore that the effectiveness of swarm intelligence is inseparable from the performance of power electronics. Therefore, scalable deployment requires co-design strategies that integrate RL-based coordination with high-efficiency converters, optimized motor control, and adaptive energy management to ensure robust, energy-aware autonomous PV maintenance systems. Furthermore, large-scale deployment in utility-scale solar farms requires addressing system scalability and ensuring compliance with grid codes and utility standards, particularly regarding interoperability, communication protocols, and grid stability integration, to enable seamless adoption in real-world energy infrastructure.

Table 2. Hardware-level challenges and technological considerations in autonomous robotic swarm systems for solar PV maintenance

Component	Key challenges	Impact on system performance	Potential solutions
Motor drive system	Nonlinear terrain interaction, variable load, energy inefficiency	Reduced mobility accuracy, increased energy consumption	Sensorless control, FOC strategies, adaptive drive algorithms
Power converter	Switching losses, EMI, suboptimal topology selection	Reduced efficiency, increased thermal stress	Wide-bandgap devices, high-frequency converters, optimized topology design
Energy storage	Battery degradation under high temperature, limited capacity	Reduced operational time, inconsistent performance	Advanced battery management systems, hybrid energy storage
Thermal management	Heat accumulation, limited cooling space	Component degradation, reduced lifespan	Passive cooling, heat sinks, and advanced thermal materials
Embedded control	Real-time processing constraints, computational load	Latency in decision-making, reduced coordination efficiency	Edge AI optimization, hardware acceleration (FPGA, ASIC)

4.2. Limitations of the literature

Although the meta-analysis provides strong evidence supporting the performance of autonomous robotic swarms, several limitations must be acknowledged to ensure accurate interpretation. Many of the included studies rely on simulated environments or controlled experimental testbeds rather than real full-scale deployments, limiting external generalizability across diverse field conditions. Variability in sensor configurations, communication protocols, and swarm coordination frameworks also introduces performance inconsistency, reflected in moderate-to-high heterogeneity index values. Additionally, limited long-term operational evidence and insufficient standardized evaluation metrics hinder comprehensive benchmarking across technologies. Most studies omit converter efficiency, motor losses, and thermal cycling in robotic systems. This creates a gap between algorithmic performance and real energy-constrained behavior, limiting comparability and industrial relevance.

4.3. Research gaps and future directions

This review identifies several critical research gaps that require attention to advance the maturity and industrial readiness of autonomous robotic swarm systems for solar farm maintenance. Empirical field validation remains limited, underscoring the need for multidisciplinary, real-world trials that integrate environmental variability, mission complexity, and long-duration operational testing. Future research should focus on developing unified performance metrics, robust fault-tolerant architectures, and adaptive multi-agent learning frameworks that can scale across large photovoltaic infrastructures. Furthermore, integrating cybersecurity protections, interoperable communication standards, and techno-economic optimization is essential to enable safe, efficient, and commercially viable deployment. Future work should model motor efficiency, switching behavior, and thermal stress. This enables realistic evaluation of swarm robotics under energy constraints and supports scalable industrial deployment.

5. CONCLUSION

This systematic review and meta-analysis establish that autonomous robotic swarms significantly enhance predictive maintenance performance in utility-scale solar PV systems by integrating decentralized coordination and multi-agent RL with edge-based intelligence. The results demonstrate consistent improvements in detection accuracy, operational efficiency, and cost reduction, confirming the effectiveness of distributed decision-making in complex and dynamic energy infrastructures. Beyond solar PV, these findings indicate broader applicability in renewable energy systems where predictive maintenance is critical, including wind farms, hybrid microgrids, and energy storage networks. The ability of swarm-based systems to operate autonomously, adapt to environmental variability, and process data locally positions them as key enablers of intelligent energy management and resilient infrastructure operations. From a systems perspective, the performance of such architectures is closely linked to power-electronics efficiency, underscoring the need to integrate control intelligence with optimized hardware design to ensure scalable, energy-aware deployment.

Despite these contributions, several challenges remain that limit large-scale implementation. The scarcity of real-world deployment studies, combined with methodological heterogeneity and the absence of standardized evaluation metrics, limits the generalizability of results and their industrial adoption. Moreover, the dominance of simulation-based studies highlights the urgent need for large-scale empirical validation under diverse environmental conditions to improve external generalizability and ensure reliable real-world performance. Future research should prioritize large-scale experimental validation under realistic operating conditions and develop unified benchmarking frameworks to enable consistent performance comparison. Additionally, integrating cybersecurity mechanisms, interoperable communication systems, and techno-economic optimization is essential to ensure reliable, commercially viable deployment. Expanding the application of swarm intelligence toward integrated renewable energy ecosystems will further strengthen its role in enabling autonomous, efficient, and sustainable predictive maintenance solutions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Mochamad Subchan Mauludin		✓				✓		✓	✓	✓	✓	✓		
Singgih Dwi Prasetyo	✓		✓	✓		✓	✓			✓	✓		✓	✓
Yuki Trisnoaji		✓			✓	✓			✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

The data used to support the research findings are available from the corresponding author upon request.

REFERENCES

[1] M. Rawa, A. Abusorrah, Y. Al-Turki, H. Sindi, H. Bassi, and M. H. Mostafa, "Efficient energy management framework for enhancing the techno-economic-environmental performance of grid-connected microgrids under uncertain conditions," *Ain Shams Engineering Journal*, vol. 15, no. 1, p. 102336, Jan. 2024, doi: 10.1016/j.asej.2023.102336.

[2] Y. M. Prianka, A. Sharma, and C. Biswas, "Integration of renewable energy, microgrids, and EV charging infrastructure: challenges and solutions," *Control Systems and Optimization Letters*, vol. 2, no. 3, pp. 317–326, Dec. 2024, doi: 10.59247/csol.v2i3.142.

[3] A. Haeruman, S. U. Haq, M. Mohandes, S. Rehman, and S. S. I. Mitu, "AI-based PV panels inspection using an advanced YOLO algorithm," in *Materials Research Proceedings*, Aug. 2024, pp. 230–237. doi: 10.21741/9781644903216-30.

[4] A. Gurras, L. Gergidis, C. Mytafides, L. Tzounis, and A. S. Paipetis, "Automated detection-classification of defects on photo-voltaic modules assisted by thermal drone inspection," *MATEC Web of Conferences*, vol. 349, p. 03015, Nov. 2021, doi: 10.1051/matecconf/202134903015.

[5] F. He, M. Zhu, J. Fan, E. Ma, S. Zhai, and H. Zhao, "Automated drone-delivery solar-driven onsite wastewater smart monitoring and treatment system," *Advanced Science*, vol. 10, no. 24, Aug. 2023, doi: 10.1002/advs.202302935.

[6] A. Hassan, S. S. U. H. Mohani, I. Y. Essani, S. A. Taj, A. Aslam, and Y. Abbas, "AI-enabled energy management for large-scale solar farms: optimizing power distribution, grid stability, and real-time performance monitoring," *PROGRESS: A Journal of Multidisciplinary Studies*, vol. 6, no. 1, pp. 66–84, 2025, doi: 10.71016/tp/vksskv66.

[7] B. Kayci, B. E. Demir, And F. Demir, "Deep learning based fault detection and diagnosis in photovoltaic system using thermal images acquired by UAV," *Politeknik Dergisi*, vol. 27, no. 1, pp. 91–99, Feb. 2024, doi: 10.2339/politeknik.1094586.

[8] M. Jemmali, A. K. Bashir, W. Boulila, L. K. B. Melhim, R. H. Jhaveri, and J. Ahmad, "An efficient optimization of battery-drone-based transportation systems for monitoring solar power plant," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 12, pp. 15633–15641, Dec. 2023, doi: 10.1109/TITS.2022.3219568.

[9] M. Li, W. Wang, H. Li, Z. Yang, and J. Li, "Monitoring of vegetation chlorophyll content in photovoltaic areas using UAV-mounted multispectral imaging," *Frontiers in Plant Science*, vol. 16, Aug. 2025, doi: 10.3389/fpls.2025.1643945.

[10] P.-Y. Lajoie and G. Beltrame, "Swarm-SLAM: Sparse decentralized collaborative simultaneous localization and mapping framework for multi-robot systems," *IEEE Robotics and Automation Letters*, vol. 9, no. 1, pp. 475–482, Jan. 2024, doi: 10.1109/LRA.2023.3333742.

[11] J. Liller, R. Goel, A. Aziz, J. Hester, and P. Nguyen, "Development of a battery free, solar powered, and energy aware fixed wing unmanned aerial vehicle," *Scientific Reports*, vol. 15, no. 1, p. 6141, Feb. 2025, doi: 10.1038/s41598-025-90729-2.

[12] S. Li, Z. Fang, S. C. Verma, J. Wei, and A. V. Savkin, "Navigation and deployment of solar-powered unmanned aerial vehicles for civilian applications: a comprehensive review," *Drones*, vol. 8, no. 2, p. 42, Jan. 2024, doi: 10.3390/drones8020042.

[13] D. Marangis, G. Tziolis, A. Livera, G. Makrides, A. Kyprianou, and G. E. Georghiou, "Intelligent maintenance approaches for improving photovoltaic system performance and reliability," *Solar RRL*, vol. 9, no. 16, Aug. 2025, doi: 10.1002/solr.202500289.

[14] P. Mahato, S. Saha, C. Sarkar, and M. Shaghil, "Consensus-based fast and energy-efficient multi-robot task allocation," *Robotics and Autonomous Systems*, vol. 159, p. 104270, Jan. 2023, doi: 10.1016/j.robot.2022.104270.

[15] O. Olayiwola, M. Elsden, and M. Dhimish, "Robotics, artificial intelligence, and drones in solar photovoltaic energy applications—safe autonomy perspective," *Safety*, vol. 10, no. 1, p. 32, Mar. 2024, doi: 10.3390/safety10010032.

[16] O. Olayiwola and F. Camara, "Challenges and opportunities for autonomous uav inspection in solar photovoltaics," *E3S Web of Conferences*, vol. 572, p. 01003, Sep. 2024, doi: 10.1051/e3sconf/202457201003.

[17] J. Morales, I. Castelo, R. Serra, P. U. Lima, and M. Basiri, "Vision-based autonomous following of a moving platform and landing for an unmanned aerial vehicle," *Sensors*, vol. 23, no. 2, p. 829, Jan. 2023, doi: 10.3390/s23020829.

[18] A. Miquela, D. Bagul, and A. A. Ezzat, "Defect detection in solar photovoltaic systems using unmanned aerial vehicles and machine learning," in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Michigan, USA: IEOM Society International, Jun. 2023. doi: 10.46254/NA8.20230375.

[19] A. Michail *et al.*, "A comprehensive review of unmanned aerial vehicle-based approaches to support photovoltaic plant diagnosis," *Heliyon*, vol. 10, no. 1, p. e23983, Jan. 2024, doi: 10.1016/j.heliyon.2024.e23983.

[20] A. Nitti, M. D. de Tullio, I. Federico, and G. Carbone, "A collective intelligence model for swarm robotics applications," *Nature Communications*, vol. 16, no. 1, p. 6572, Jul. 2025, doi: 10.1038/s41467-025-61985-7.

[21] Y. Zhou, A. Chen, X. He, and X. Bian, "Multi-target coordinated search algorithm for swarm robotics considering practical constraints," *Frontiers in Neurorobotics*, vol. 15, Dec. 2021, doi: 10.3389/fnbot.2021.753052.

[22] G. E. Mustafa Abro, A. Ali, S. Ali Memon, T. Din Memon, and F. Khan, "Strategies and challenges for unmanned aerial vehicle-based continuous inspection and predictive maintenance of solar modules," *IEEE Access*, vol. 12, pp. 176615–176629, 2024, doi: 10.1109/ACCESS.2024.3505754.

[23] I. Kishor, U. Mamodiya, V. Patil, and N. Naik, "AI-Integrated autonomous robotics for solar panel cleaning and predictive maintenance using drone and ground-based systems," *Scientific Reports*, vol. 15, no. 1, p. 32187, Sep. 2025, doi: 10.1038/s41598-025-17313-6.

[24] K. Bojappa and J. Lee, "Review on particle swarm optimization: application toward autonomous dynamical systems," *IEEE/CAA Journal of Automatica Sinica*, vol. 12, no. 9, pp. 1762–1775, Sep. 2025, doi: 10.1109/JAS.2024.125028.

[25] P. Tugwell and D. Tovey, "PRISMA 2020," *Journal of Clinical Epidemiology*, vol. 134, pp. A5–A6, Jun. 2021, doi: 10.1016/j.jclinepi.2021.04.008.

[26] M. Sherman, M. Gammill, A. Raissi, and M. Hassanalian, “Solar UAV for the inspection and monitoring of photovoltaic (pv) systems in solar power plants,” in *AIAA Scitech 2021 Forum*, Reston, Virginia: American Institute of Aeronautics and Astronautics, Jan. 2021. doi: 10.2514/6.2021-1683.

[27] E. A. Ramadan, N. M. Moawad, B. A. Abouzalm, A. A. Sakr, W. F. Abouzaid, and G. M. El-Banby, “An innovative transformer neural network for fault detection and classification for photovoltaic modules,” *Energy Conversion and Management*, vol. 314, p. 118718, Aug. 2024, doi: 10.1016/j.enconman.2024.118718.

[28] Y. Pei, Y. Yao, J. Zhao, F. Ding, and J. Wang, “Multi-agent deep reinforcement learning for realistic distribution system voltage control using PV inverters,” in *2022 IEEE Power & Energy Society General Meeting (PESGM)*, IEEE, Jul. 2022, pp. 1–5. doi: 10.1109/PESGM48719.2022.9917152.

[29] L. Wang, H. Wu, Y. Yu, W. Yu, S. Chen, and J. Wang, “Gate-conv SVDD: An anomaly detection framework for fault inspection of photovoltaic panels using UAVs,” *IEEE Internet of Things Journal*, vol. 12, no. 19, pp. 41103–41117, Oct. 2025, doi: 10.1109/JIOT.2025.3591635.

[30] R. V. Vichare and S. R. Gaikwad, “AI-based predictive maintenance of solar photovoltaics systems: a comprehensive review,” *Energy Informatics*, vol. 8, no. 1, p. 128, Oct. 2025, doi: 10.1186/s42162-025-00594-6.

[31] J.-T. Zou and G. V. Rajveer, “Drone-based solar panel inspection with 5G and AI technologies,” in *2022 8th International Conference on Applied System Innovation (ICASI)*, IEEE, Apr. 2022, pp. 174–178. doi: 10.1109/ICASI55125.2022.9774462.

[32] S. J. Carlson, P. Arora, and C. Papachristos, “Towards Perpetually-Deployable Ubiquitous Aerial Robotics: An Amphibious Self-Sustainable Solar Small-UAS,” in *2025 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, May 2025, pp. 295–302. doi: 10.1109/ICRA55743.2025.11127506.

[33] Y. Zhou *et al.*, “Three dimensional fully autonomous inspection method for wind power employing unmanned aerial vehicle based on 5G wireless communication and artificial intelligence,” in *2022 IEEE 5th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, IEEE, Dec. 2022, pp. 800–805. doi: 10.1109/IMCEC55388.2022.10019897.

[34] X. Zhang *et al.*, “Inspection and classification system of photovoltaic module defects based on UAV and thermal imaging,” in *2022 7th International Conference on Power and Renewable Energy (ICPRE)*, IEEE, Sep. 2022, pp. 905–909. doi: 10.1109/ICPRE55555.2022.9960506.

[35] Z. Wang, P. Zheng, B. Bahadir Kocer, and M. Kovac, “Drone-based solar cell inspection with autonomous deep learning,” in *Infrastructure Robotics*, Wiley, 2024, pp. 337–365. doi: 10.1002/9781394162871.ch16.

[36] A. Gopi, P. Sharma, K. Sudhakar, W. K. Ngui, I. Kirpichnikova, and E. Cuce, “Weather impact on solar farm performance: a comparative analysis of machine learning techniques,” *Sustainability*, vol. 15, no. 1, p. 439, Dec. 2022, doi: 10.3390/su15010439.

[37] A. Ghalazman E. *et al.*, “Applications of robotic and solar energy in precision agriculture and smart farming,” in *Solar Energy Advancements in Agriculture and Food Production Systems*, Elsevier, 2022, pp. 351–390. doi: 10.1016/B978-0-323-89866-9.00011-0.

[38] D. Cerdeira, R. Bettencourt, and A. Vale, “Optimizing mobile robot fleet distributions in solar farms,” in *2025 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, IEEE, Apr. 2025, pp. 9–14. doi: 10.1109/ICARSC65809.2025.10970171.

[39] M. Dhimish and A. M. Tyrrell, “Photovoltaic bypass diode fault detection using artificial neural networks,” *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–10, 2023, doi: 10.1109/TIM.2023.3244230.

[40] G. Cipriani, D. Manno, V. Di Dio, and M. Traverso, “Thermal anomalies detection in a photovoltaic plant using artificial intelligence: Italy case studies,” in *2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*, IEEE, Sep. 2021, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584494.

[41] M. M. Shahzad *et al.*, “A review of swarm robotics in a NutShell,” *Drones*, vol. 7, no. 4, p. 269, Apr. 2023, doi: 10.3390/drones7040269.

[42] H. Bakır, F. A. Kuzhippallil, and A. Merabet, “Automatic detection of deteriorated photovoltaic modules using IRT images and deep learning (CNN, LSTM) strategies,” *Engineering Failure Analysis*, vol. 146, p. 107132, Apr. 2023, doi: 10.1016/j.engfailanal.2023.107132.

[43] A. Ghobadpour, A. Cardenas, G. Monsalve, and H. Mousazadeh, “Optimal design of energy sources for a photovoltaic/fuel cell extended-range agricultural mobile robot,” *Robotics*, vol. 12, no. 1, p. 13, Jan. 2023, doi: 10.3390/robotics12010013.

[44] J. Dvorak and B. Smith, “Powering in-field continuous robotic systems using solar energy systems,” *Journal of the ASABE*, vol. 67, no. 3, pp. 617–630, 2024, doi: 10.13031/ja.15579.

[45] M. Kondoyanni, D. Loukatos, C. Maraveas, C. Drosos, and K. G. Arvanitis, “Bio-inspired robots and structures toward fostering the modernization of agriculture,” *Biomimetics*, vol. 7, no. 2, p. 69, May 2022, doi: 10.3390/biomimetics7020069.

[46] G. Abhinav, G. Harshavardhan, S. Pavani, G. Vishnuvardhan, K. Natarajan, and M. Krishnamoorthy, “Automated drone-based solar panel cleaning for enhanced efficiency and sustainable solar power generation,” in *2025 5th International Conference on Trends in Material Science and Inventive Materials (ICTMIM)*, IEEE, Apr. 2025, pp. 266–271. doi: 10.1109/ICTMIM65579.2025.10988167.

[47] D. Marek *et al.*, “Swarm of drones in a simulation environment—efficiency and adaptation,” *Applied Sciences*, vol. 14, no. 9, p. 3703, Apr. 2024, doi: 10.3390/app14093703.

[48] X. Li, H. Huang, A. Savkin, and J. Zhang, “Robotic herding of farm animals using a network of barking aerial drones,” *Drones*, vol. 6, no. 2, p. 29, Jan. 2022, doi: 10.3390/drones6020029.

[49] Y. Zefri, I. Sebari, H. Hajji, and G. Aniba, “Developing a deep learning-based layer-3 solution for thermal infrared large-scale photovoltaic module inspection from orthorectified big UAV imagery data,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 106, p. 102652, Feb. 2022, doi: 10.1016/j.jag.2021.102652.

[50] S. S. Akay, O. Özcan, O. Özcan, and Ö. Yetemen, “Efficiency analysis of solar farms by UAV-based thermal monitoring,” *Engineering Science and Technology, an International Journal*, vol. 53, p. 101688, May 2024, doi: 10.1016/j.jestch.2024.101688.

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