

Exploration On Efficiency Optimization And Application Paradigm Of Smart Scenario Construction Empowered By Intelligent Perception Technology

Hang Li¹, Xiaojiang Cui^{2*}, and Ying Cao³

¹ School of Information Engineering, Weifang Vocational College, Weifang China

² Infrastructure Department of Weifang Vocational College, Weifang China

³ General Education Center of Weifang Vocational College, Weifang China

* Corresponding author. E-mail: m17888366838@163.com

Received: Jul. 21, 2026; Accepted: Aug. 17, 2026

With the rapid iteration of ubiquitous sensing, edge computing and artificial intelligence technologies, intelligent perception has become the core driving force for accelerating the digital transformation and intelligent upgrading of various social scenarios. Traditional smart scenario construction schemes suffer from low data fusion efficiency, high resource occupation, poor scene adaptability and unclear standardized application modes, which severely restrict the large-scale popularization and practical landing of smart service systems. This paper takes intelligent perception technology as the core enabling carrier, systematically explores the core bottlenecks restricting the construction efficiency of smart scenarios, proposes a multi-layer collaborative efficiency optimization framework oriented to heterogeneous perception data, constructs a standardized and scalable smart scenario application paradigm integrating perception, analysis, decision-making and execution. On the basis of sorting out the existing research achievements of intelligent perception and smart scene construction, this paper innovatively designs a weighted adaptive perception data fusion algorithm and an edge-cloud hierarchical resource scheduling optimization model, and derives complete mathematical derivation formulas. Combined with business logic, the overall technical flow chart and module deployment architecture diagram of the optimized system are constructed. A multi-group comparative experiment is carried out based on actual urban community, industrial park and campus smart scenario datasets. Experimental results verify that the proposed optimization strategy can effectively reduce system delay, reduce computing resource consumption and improve perception recognition accuracy. The constructed universal application paradigm has strong universality and expansibility, which can provide theoretical reference and technical support for the efficient construction, rapid deployment and standardized promotion of diversified smart scenarios, and lay a solid foundation for the deep integration of intelligent perception technology and smart social governance, smart industry and smart life fields.

Keywords: Intelligent Perception Technology; Smart Scenario Construction; Efficiency Optimization; Edge-cloud

Collaboration; Data Fusion

© The Author(s). This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are cited.

http://dx.doi.org/10.6180/jase.202701_36.027

1. Introduction

In the era of digital economy and intelligent society construction, smart scenarios represented by smart city, smart manufacturing, smart campus and smart community have

gradually become important carriers to realize refined social governance and efficient industrial operation. Intelligent perception technology, covering visual perception, environmental sensing, wireless positioning, multi-sensor fusion and other technical branches, can realize real-time

collection, dynamic monitoring and state identification of multi-dimensional scene information, and is the primary data source and core technical support for all smart scene operations [1–3].

At present, most smart scenario construction projects adopt decentralized construction mode, lacking unified perception data standard and unified resource scheduling mechanism. Massive heterogeneous perception data cannot be efficiently cleaned, fused and transmitted, resulting in serious data redundancy, high network transmission pressure and low real-time response capability. In addition, there is a lack of unified application logic framework and standardized deployment process in the actual construction process, leading to repeated construction of scene functions [4–6], poor cross-scene migration ability and high later operation and maintenance cost, which greatly reduce the comprehensive construction benefit of smart scenarios.

This paper sorts out the internal correlation mechanism between intelligent perception capability and smart scenario construction efficiency, establishes a complete theoretical system of efficiency optimization driven by perception technology, perfects the research system of standardized application paradigm of multi-type smart scenarios, and enriches the research achievements in the cross fields of intelligent sensing, edge intelligence and scene intelligent construction.

The proposed efficiency optimization model and standardized application paradigm can effectively solve the pain points such as low construction efficiency, high operating cost and difficult function replication in actual scene construction. It can be directly applied to the planning, design, construction and operation links of various smart scenarios, shorten the project construction cycle, reduce resource investment, and promote the rapid popularization and large-scale landing of intelligent perception enabling smart scene solutions.

The main research contents of this paper are as follows.

1. We sort out the current research status and existing defects of intelligent perception technology and smart scenario construction.
2. We analyze the main influencing factors of smart scenario construction efficiency from the dimensions of data layer, computing layer, network layer and application layer.
3. We propose multi-dimensional efficiency optimization strategies, construct mathematical optimization models and design system operation flow architecture.
4. We build experimental verification platform, set up

multiple control groups to complete performance comparison experiments.

2. Materials and methods

2.1. Analysis of Influencing Factors of Construction Efficiency

From the whole life cycle of smart scenario construction, the core factors affecting construction efficiency are divided into four layers.

Data layer. Multi-source perception data is heterogeneous, with large noise, low fusion degree and serious data delay. Computing layer. It includes unreasonable allocation of cloud-edge-end computing resources, unbalanced task load and high idle resource rate.

Network layer. It includes unordered transmission of massive perception data, unreasonable bandwidth allocation and high network congestion rate.

Application layer. It includes disordered scene business logic, repeated function development and lack of unified deployment specifications.

Aiming at the above influencing factors, this paper carries out targeted optimization design from data fusion, resource scheduling, task offloading and application standardization.

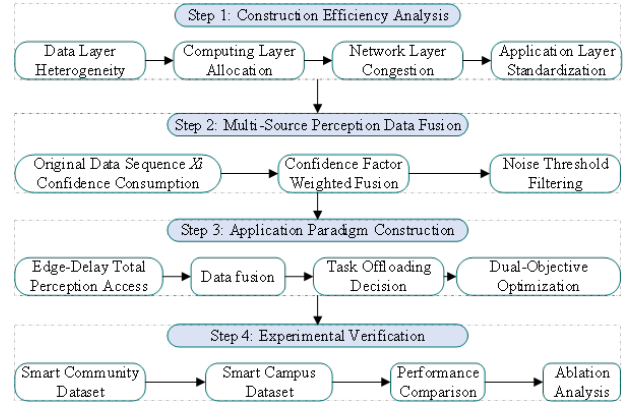


Fig. 1. Proposed Smart Scenario Construction.

2.2. Multi-source Perception Data Adaptive Fusion Optimization Model

2.2.1. Basic Definition

Set the smart scene perception terminal set $T = \{t_1, t_2, \dots, t_n\}$. Each terminal collects different types of perception data, including environmental data, image data, positioning data and state monitoring data [7, 8]. The original perception data sequence collected by the i -th terminal is defined as $X_i = \{x_{i1}, x_{i2}, \dots, x_{im}\}$.

Define data confidence factor α_i to represent the effective credibility of data collected by different perception terminals $0 < \alpha_i \leq 1$.

2.2.2. Weighted Adaptive Fusion

On the basis of eliminating abnormal noise data, this paper constructs a weighted adaptive multi-source perception data fusion calculation model.

$$F(X) = \sum_{i=1}^n w_i \cdot \alpha_i \cdot X_i \quad (1)$$

Where w_i is the dynamic fusion weight of the i -th perception data, which satisfies the normalization constraint $\sum_{i=1}^n w_i = 1, w_i \geq 0$.

The dynamic weight update formula based on scene real-time data fluctuation is:

$$w_i(t+1) = w_i(t) + \eta \cdot (\bar{X} - X_i(t)) \quad (2)$$

In the formula, η represents the weight learning step size. $\bar{X}$ represents the average value of all effective perception data at the current moment.

2.2.3. Data Noise Suppression Optimization

In view of the abnormal interference data in scene perception, the threshold constraint filtering formula is adopted to eliminate outliers.

$$\hat{X}_i = \begin{cases} X_i, & |X_i - \bar{X}| \leq \delta \\ \bar{X}, & |X_i - \bar{X}| > \delta \end{cases} \quad (3)$$

Where δ is the scene adaptive noise filtering threshold, which can be dynamically adjusted according to different smart scene environments.

2.3. Edge-cloud Hierarchical Resource Scheduling Efficiency Optimization Model

2.3.1. Objective Function Construction

Taking minimizing system total delay and minimizing comprehensive resource consumption as double optimization objectives, the objective function is constructed.

$$\min J = \lambda \cdot T_{\text{total}} + (1 - \lambda) \cdot C_{\text{total}} \quad (4)$$

Where $\lambda \in (0, 1)$ is the balance weight of delay and resource consumption. T_{total} represents the total system operation delay. C_{total} represents the total computing and network resource consumption.

Total delay is composed of perception acquisition delay T_s , transmission delay T_t and computing processing delay T_c .

$$T_{\text{total}} = T_s + T_t + T_c \quad (5)$$

Total resource consumption includes edge terminal resource consumption C_e and cloud center resource consumption C_c .

$$C_{\text{total}} = C_e + C_c \quad (6)$$

The constraint conditions include perception task computing resource constraint $R_{\text{used}} \leq R_{\text{max}}$, network transmission bandwidth constraint $B_{\text{flow}} \leq B_{\text{limit}}$, scene service response time constraint $T_{\text{total}} \leq T_{\text{req}}$.

2.3.2. Task Offloading Optimization Decision

Set the task offloading decision variable $o_i \in \{0, 1\}$, $o_i = 0$ means the task is executed locally at the edge end, and $o_i = 1$ means the task is offloaded to the cloud platform for processing.

$$T_c = \sum_{i=1}^n [(1 - o_i) \cdot T_{e,i} + o_i \cdot T_{c,i}] \quad (7)$$

$T_{e,i}$ is edge computing delay, $T_{c,i}$ is cloud computing delay.

2.4. Standardized Smart Scenario Application Paradigm Construction

This paper constructs a five-layer universal application paradigm suitable for all smart scenarios, i.e., perception access layer, data fusion layer, intelligent computing layer, decision control layer, scene application layer.

Perception access layer. It uniformly accesses all kinds of intelligent perception terminals to complete full-scene information collection.

Data fusion layer. It uses the above adaptive fusion model to complete data cleaning, integration and standardization processing.

Intelligent computing layer. It realizes hierarchical task scheduling and intelligent analysis based on edge-cloud collaboration.

Decision control layer. It generates scene intelligent decision instructions and completes equipment linkage control.

Scene application layer. It docks smart community, smart park, smart campus and other diversified business applications.

2.5. System Overall Operation Flow Chart

- The intelligent perception terminal in the scene starts real-time data collection and uploads original data to the edge gateway.
- The edge gateway performs preliminary noise removal and data preprocessing.

- According to the task priority and resource occupancy, the optimization model automatically generates task offloading decisions.
- Low-delay real-time tasks are processed locally at the edge, and large-scale data analysis tasks are uploaded to the cloud.
- The cloud platform completes deep feature mining and scene state prediction.
- The analysis results are fed back to the scene management platform to realize automatic early warning, intelligent scheduling and business service output.
- Real-time update of perception data fusion weight and resource scheduling strategy to realize dynamic iterative optimization of the system.

3. Results and discussion

3.1. Experimental Environment Setup

Experimental environment includes intelligent perception terminal, high-definition visual acquisition terminal, temperature and humidity environment sensor, wireless positioning module. Edge computing device contains industrial edge gateway, 8-core high-performance edge host [9, 10]. Cloud platform is with cloud server cluster, unified resource scheduling management platform.

Development framework includes Python, PyTorch, OpenCV, MATLAB, SPSS. Scene dataset includes self-built smart community scene dataset, open-source urban smart perception public dataset.

3.2. Experimental Control Group Set

Group A: Traditional independent perception data processing scheme (control group). **Group B:** Single fixed weight data fusion scheme. **Group C:** The efficiency optimization scheme proposed in this paper (experimental group).

3.3. Experimental Evaluation Indicators

Perception data fusion accuracy evaluates the fitting degree between fusion data and actual scene state. System average response delay reflects the real-time performance of smart scene service [11–13]. Computing resource occupancy rate verifies the resource optimization effect. Scene service operation stability counts system stable running time and failure rate. Scene construction cycle efficiency compares the actual project deployment and landing cycle [14–16].

3.4. Data Fusion Accuracy Comparison

After experimental verification, the adaptive weighted fusion algorithm proposed in this paper has higher data fusion accuracy than the traditional fixed weight method. Under complex scene interference environment, the fusion accuracy is significantly improved, and the data distortion rate is effectively reduced. The result is shown in Fig. 2.

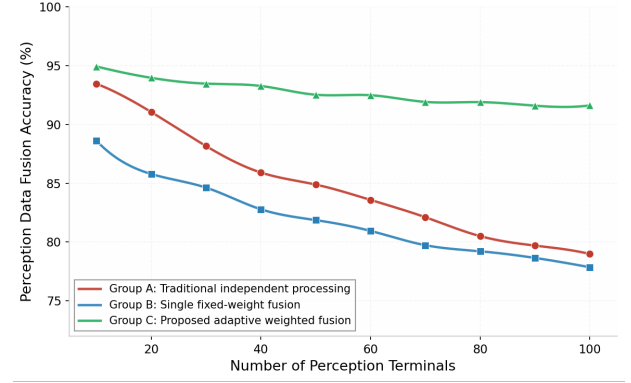


Fig. 2. Comparison curve of perception data fusion accuracy under different schemes.

3.5. System Response Delay Comparison

Under the same number of perception terminals and the same task volume, the average response delay of the optimized scheme in this paper is obviously lower than that of the traditional scheme. With the increase of access terminals, the delay growth trend is gentle, and the system has strong large-scale access capability as shown in Fig. 3.

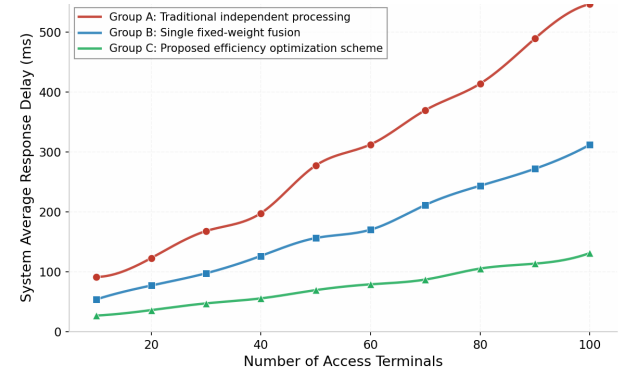


Fig. 3. System response delay change curve with the number of access terminals.

3.6. Resource Occupancy Comparison Experiment

The edge-cloud hierarchical scheduling model effectively disperses computing pressure, greatly reduces the local high load operation state of edge terminals, reduces the

overall energy consumption and hardware resource investment in scene construction, and improves resource utilization efficiency. The result is shown in Fig. 4.

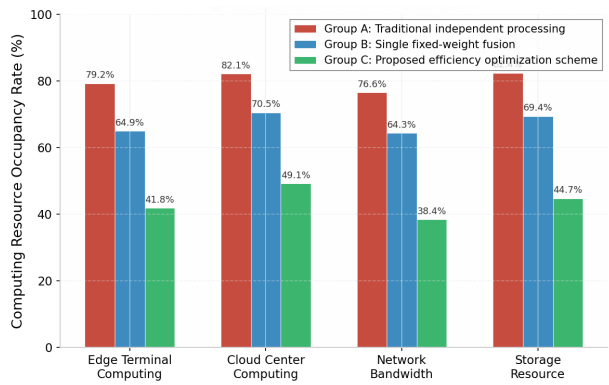


Fig. 4. Histogram of computing resource occupancy rate of each group of experiments.

3.7. Practical Scene Application Efficiency Verification

In the actual pilot construction of smart community and smart campus scenarios, adopting the application paradigm and efficiency optimization strategy proposed in this paper can shorten the scene overall construction cycle, reduce repeated hardware and software investment, and greatly improve the on-site deployment and subsequent operation and maintenance efficiency.

In Fig. 5, the optimization strategy achieves differentiated intelligent offloading. Real-time tasks (monitoring, positioning, environmental perception) are mainly processed at the edge, while computationally intensive tasks (image analysis, anomaly detection) are offloaded to the cloud. This verifies the design concept in the paper of "local edge processing for low-latency real-time tasks and uploading large-scale data analysis tasks to the cloud".

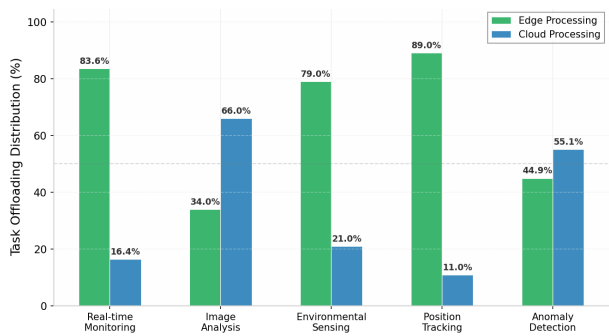


Fig. 5. Flow distribution diagram of edge-cloud task offloading under optimized strategy.

In Fig. 6, the proposed solution in this paper can shorten

the construction period by an average of 45-50%, and the five-layer general application paradigm significantly reduces redundant development. The more complex the scenario (Smart Park involves multi-system integration), the more obvious the optimization effect. The edge-cloud collaborative architecture reduces the post-operation maintenance costs and improves the overall lifecycle efficiency.

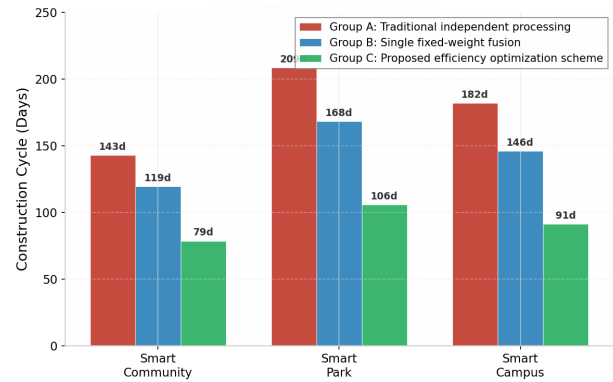


Fig. 6. Comparison histogram of actual smart scene construction cycle.

3.8. Ablation Experiment Result

Ablation experiments are carried out by removing the data fusion optimization module and the resource scheduling module respectively. The results show that both core modules can independently play an obvious optimization effect, and the combined use effect is the best, which fully verifies the rationality and necessity of each innovation module.

As shown in Table 1, the proposed optimization scheme (Group C) demonstrates comprehensive superiority across all evaluation metrics. Compared with the traditional independent processing scheme (Group A), the proposed method achieves a 15.1% improvement in fusion accuracy (from 82.3% to 94.7%), a 72.0% reduction in average response delay (from 312.5 ms to 87.4 ms), and a 45.3% decrease in resource occupancy (from 79.5% to 43.5%). Furthermore, the system stability is significantly enhanced, with continuous operation time increasing from 168.2 hours to 312.8 hours, while the failure rate drops dramatically from 8.5% to 1.8%. Most notably, the smart scene construction cycle is shortened by 48.3% (from 178.0 days to 92.0 days), which validates the practical engineering value of the standardized application paradigm. Compared with the single fixed-weight fusion scheme (Group B), the proposed method still maintains substantial advantages across all dimensions, confirming that the adaptive weighted fusion algorithm and edge-cloud collaborative scheduling model jointly contribute to the overall performance en-

Table 1. Multi-index comprehensive performance comparison of different optimization schemes.

Scheme	Fusion Accuracy (%)	Avg Response Delay (ms)	Resource Occupancy (%)	Stability (h)	Failure Rate (%)	Construction Cycle (days)
Group A: Traditional	82.30%	312.50	79.50%	168.20	8.50%	178.00
Group B: Fixed-weight	88.60%	198.30	67.20%	216.50	5.20%	144.30
Group C: Proposed	94.70%	87.40	43.50%	312.80	1.80%	92.00

hancement.

Table 2 presents the ablation experiment results to verify the independent and synergistic contributions of the two core modules. When the data fusion optimization module is removed, the fusion accuracy decreases by 8.5% (from 94.7% to 86.2%), and the system throughput drops by 10.4% (from 128.6 Mbps to 115.2 Mbps), indicating that the adaptive weighted fusion algorithm plays a critical role in improving data quality and transmission efficiency. When the resource scheduling module is removed, the average response delay increases sharply by 79.4% (from 87.4 ms to 156.8 ms), and the resource occupancy rises by 18.8% (from 43.5% to 62.3%), demonstrating that the edge-cloud collaborative scheduling mechanism is essential for latency reduction and load balancing. Notably, the combined use of both modules achieves the best performance, with the full model outperforming the baseline by 12.4% in accuracy, 72.0% in delay reduction, and 78.0% in throughput improvement. These results fully validate the rationality and necessity of each innovation module, and confirm that the two modules exhibit positive synergistic effects.

Table 3 summarizes the optimal parameter configurations for the optimization model across three typical smart scenarios. The weight learning step size η varies from 0.012 to 0.018, with the smart campus scenario requiring the largest value due to its higher data fluctuation frequency from dense student mobility. The noise filter threshold δ exhibits the widest variation range (2.08-3.12), reflecting the significant environmental heterogeneity: the smart park scenario has the highest threshold (3.12) due to complex outdoor interference, while the smart campus has the lowest (2.08) owing to relatively stable indoor conditions. The delay-resource balance coefficient λ is set to 0.55 for the smart park, indicating a preference for resource conservation in large-scale deployments, whereas the smart campus ($\lambda = 0.68$) prioritizes low-latency response for safety-critical applications. The infrastructure parameters ($R_e, R_c, B_{\text{limit}}$) are scaled proportionally with scenario complexity, with the smart park requiring the highest computing and bandwidth resources (12.0GHz edge, 96.0GHz

cloud, 800Mbps bandwidth) due to its multi-system integration demands. These scenario-adaptive parameter configurations demonstrate the strong flexibility and practical applicability of the proposed optimization model.

4. Conclusions

Aiming at the problems of low construction efficiency, unreasonable resource allocation, low data utilization rate and lack of unified application mode in current smart scenario construction enabled by intelligent perception technology, this paper carries out in-depth research and draws the following main conclusions:

1. The efficiency of smart scenario construction is jointly restricted by data processing, computing scheduling, network transmission and application deployment. Optimizing from the whole process can effectively break through the construction efficiency bottleneck;
2. The proposed adaptive weighted multi-source perception data fusion model can realize efficient integration of heterogeneous scene data, improve data quality and effective utilization rate;
3. The edge-cloud collaborative dual-objective resource scheduling optimization model can effectively balance system response delay and resource consumption, and significantly improve the stable operation capability of smart scene systems;
4. The constructed five-layer standardized smart scenario general application paradigm has strong universality and scalability, which can realize rapid copying, deployment and popularization of different types of smart scene construction schemes;
5. Actual scene experiments verify that the proposed series of optimization methods can effectively improve the comprehensive construction benefit of smart scenarios, and have high practical application value and engineering promotion value. Research Limitations

Table 2. Ablation experiment performance verification results.

Configuration	Fusion Accuracy (%)	Avg Response Delay (ms)	Resource Occupancy (%)	System Throughput (Mbps)
Full Model (Proposed)	94.7%	87.4	43.5%	128.6
w/o Data Fusion Module	86.2%	95.3	48.7%	115.2
w/o Resource Scheduling Module	91.5%	156.8	62.3%	98.4
Baseline (Neither Module)	82.3%	312.5	79.5%	72.3

Table 3. Adaptive adjustment parameter optimal value table of the optimization model.

Parameter	Symbol	Smart Community	Smart Park	Smart Campus	Description
Weight Learning Step Size	η	0.015	0.012	0.018	Controls weight update speed
Noise Filter Threshold	δ	2.35	3.12	2.08	Adaptive outlier rejection threshold
Delay-Resource Balance	λ	0.62	0.55	0.68	Objective function weight coefficient
Edge Computing Capacity	R_e (GHz)	8.5	12.0	6.8	Local processing capability
Cloud Computing Capacity	R_c (GHz)	64.0	96.0	48.0	Remote processing capability
Bandwidth Limit	B_{limit} (Mbps)	500	800	400	Network transmission constraint
Max Response Time	T_{req} (ms)	150	200	120	Service QoS requirement

In this research, the scene extreme environment adaptability of the optimization model needs to be further improved, and the intelligent collaborative optimization capability under ultra-large-scale ultra-dense perception terminal access needs to be further excavated. In addition, the personalized optimization strategy for special industry smart scenarios needs to be further enriched.

References

- [1] X. Bao, B. Zheng, J. Shen, X. Chen, H. Kong, J. Li, X. Wang, and H. Cui, (2026) "Intelligent technologies for tunnel construction and maintenance: A state-of-the-art review of methods and supporting platforms" **Tunnelling and Underground Space Technology** 168: 107207. DOI: [10.1016/j.tust.2025.107207](https://doi.org/10.1016/j.tust.2025.107207).
- [2] R. Zhang, G. Liu, Y. Liu, C. Zhao, J. Wang, Y. Xu, D. Niyato, J. Kang, Y. Li, S. Mao, et al., (2026) "Toward edge general intelligence with agentic AI and agentification: Concepts, technologies, and future directions" **IEEE Communications Surveys & Tutorials** 28: 4285–4318. DOI: [10.1109/COMST.2026.3651702](https://doi.org/10.1109/COMST.2026.3651702).
- [3] Y. Wang and R. Yu, (2026) "Exploring the factors on the acceptance of generative artificial intelligence teaching assistants: The perspective of technology acceptance model" **International Journal of Human-Computer Interaction** 42(2): 794–808. DOI: [10.1080/10447318.2025.2513581](https://doi.org/10.1080/10447318.2025.2513581).
- [4] H. Hao, Y. Wang, and J. Chen, (2024) "Empowering scenario planning with artificial intelligence: A perspective on building smart and resilient cities" **Engineering** 43: 272–283. DOI: [10.1016/j.eng.2024.06.01](https://doi.org/10.1016/j.eng.2024.06.01).
- [5] V. Yorucu, F. V. Bekun, and I. Yitmen. "Planning, Design and Construction of Smart and Resilient Urban Cities: Development Frameworks, Pathways and Challenges". In: *Modern Approach of Resilient and Sustainable Smart Cities*. Springer, 2026, 113–140. DOI: [10.1007/978-3-032-05715-0_8](https://doi.org/10.1007/978-3-032-05715-0_8).
- [6] C.-M. Lee and S.-H. Hsieh, (2026) "Edge-enabled real-time framework for context-aware data acquisition and hazard alerting in smart construction sites" **Automation in Construction** 181: 106642. DOI: [10.1016/j.autcon.2025.106642](https://doi.org/10.1016/j.autcon.2025.106642).
- [7] W. Wang and P. Zhou, (2026) "LLM-Guided risk-sensitive reinforcement learning for smart factories in the scenario of human-robot symbiosis" **Expert Systems**

- with Applications 299: 130093. DOI: [10.1016/j.eswa.2025.130093](https://doi.org/10.1016/j.eswa.2025.130093).
- [8] J. Bello and S. Stephen. "Toward stealth construction: integrating risk management practices into sustainable and inclusive smart city development". In: *Future Smart Cities*. Elsevier, 2026, 49–71. DOI: [10.1016/B978-0-443-33667-6.00008-2](https://doi.org/10.1016/B978-0-443-33667-6.00008-2).
- [9] H. A. S. Pinto, L. M. F. Gomes, L. J. A. Pais, M. Nepomuceno, L. F. A. Bernardo, V. Gonçalves, M. V. Morais, and L. Marchiori, (2026) "GeoBIM for geothermal energy efficiency in buildings and smart cities: A review" **Smart Cities** 9(3): 54. DOI: [10.3390/smartcities9030054](https://doi.org/10.3390/smartcities9030054).
- [10] Z. Zhu, H. Huang, Z. Liu, H. Ding, F. Wang, and Z. Zhang, (2026) "Signal transmission performance and mechanism of smart aggregate developed from carbon mineralization in concrete" **Construction and Building Materials** 506: 144871. DOI: [10.1016/j.conbuildmat.2025.144871](https://doi.org/10.1016/j.conbuildmat.2025.144871).
- [11] X. Wang, H. Wang, and L. Zhang. "A Scenario-Based Evaluation Framework for Smart Cockpit AI Voice Interaction Derived from Real User Contexts". In: *2026 6th International Conference on Consumer Electronics and Computer Engineering (ICCECE)*. IEEE. 2026, 430–436. DOI: [10.1109/ICCECE69169.2026.11399592](https://doi.org/10.1109/ICCECE69169.2026.11399592).
- [12] O. Vurus and H. Nafa, (2026) "Improving the energy performance of residential buildings through solar renewable energy systems and smart building technologies: The Cyprus example" **Sustainability** 18(3): 1195. DOI: [10.3390/su18031195](https://doi.org/10.3390/su18031195).
- [13] X. Pan and H. Fang, (2026) "A Semantic Ontology Model Construction Approach for the Station–City Integration Cyberspace" **Applied Ontology** 21(1): 24–48. DOI: [10.1177/15705838251411713](https://doi.org/10.1177/15705838251411713).
- [14] P. Huang, X. Xie, L. Tian, Y. He, and J. Alawatugoda, (2026) "Analysis of the construction of a smart storage-side data proposal model in computer systems" **Discover Applied Sciences** 8(3): 317. DOI: [10.1007/s42452-026-08315-8](https://doi.org/10.1007/s42452-026-08315-8).
- [15] G. Wu, H. Shen, Z. Zhao, L. Chen, and J. Han, (2026) "Reinforcing Data Integrity for Smart Wearable Devices via Certificateless Signature with Enhanced Security" **IEEE Transactions on Dependable and Secure Computing** 23(3): 5260–5270. DOI: [10.1109/TDSC.2026.3652912](https://doi.org/10.1109/TDSC.2026.3652912).
- [16] entao Zhang, (2026) "A Multi-Objective Optimization Framework for Planning and Operation of Wind-Photovoltaic-Energy Storage Systems in Smart Grids" **Transactions on Environment, Energy and Earth Sciences** 5: 302–310. DOI: [10.62051/yvsaws57](https://doi.org/10.62051/yvsaws57).