ISSN: 2710-0588

Research on Cross-domain Data Fusion and Co-optimization Strategy of Smart City Management Software

Tao Lin[1, a]

[1]TONGFANG TECHNOVATOR INT. (BEIJING) CO., LTD., Beijing, China

[a]gongzuo1232024@126.com

Abstract

In order to enhance the collaborative capability of smart cities in multi-domain resource scheduling and dynamic governance, we construct cross-domain data fusion and optimization strategies for transportation, energy, security and other domains, and study the standardized modeling of heterogeneous data from multiple sources, the edge-cloud collaborative fusion mechanism and the optimization method of deep reinforcement learning under multi-intelligent body system. We analyze the security guarantee effectiveness of federated learning, differential privacy and other techniques in data sharing, and propose a system architecture that can realize low-latency response and efficient collaboration in complex urban scenarios. The constructed model significantly improves the decision-making efficiency and robustness of the system under the actual operation data of multiple cities, and effectively alleviates the problems of data silo and policy mismatch in traditional urban management.

Keywords

Smart city; cross-domain data fusion; multi-intelligent body system; real-time collaborative optimization.

1. Introduction

With the acceleration of urbanization, the construction of smart cities continues to deepen globally, and data-driven has become the core kinetic energy to improve the operational efficiency and governance capacity of cities. As a key platform to support urban resource allocation, public service optimization and security risk response, smart city management software's ability to integrate and synergize data from multiple fields is directly related to the responsiveness and refinement level of the governance system. However, the current problems of data dispersion, inconsistent standards, and semantic heterogeneity among urban transportation, energy, security, and other systems are prominent, restricting the improvement of the overall performance. This study aims to construct a set of cross-domain data fusion and collaborative optimization strategies for smart city scenarios, to solve the technical bottleneck of multi-source heterogeneous data integration, to realize the efficient collaboration of inter-departmental resource scheduling and dynamic decision-making, and to focus on the systematic solution paths for the key challenges of format heterogeneity, time guarantee and privacy protection.

2. Literature Review

2.1. State of the art in cross-domain data fusion

In recent years, fusion techniques such as federated learning, knowledge graph and multimodal data alignment have made significant progress in data integration practices in smart cities.Zou et al. (2025) proposed a deep learning-driven cross-domain fusion model to improve the

ISSN: 2710-0588

accuracy of urban traffic prediction and energy scheduling while preserving local privacy, but the algorithm is sensitive to communication bandwidth and model synchronization, and is susceptible to fluctuations in edge node performance [Fadhel et al. (2024) systematically combed through multi-source data fusion methods and pointed out that semantic inconsistency and lack of real-time are still the key bottlenecks constraining multi-domain collaboration.Li et al. (2023) constructed an integrated IoT platform architecture for city clusters, which initially realized heterogeneous data scheduling across hierarchical levels and systems, but suffered from the problem of structural matching latency in highly dynamic scenarios [2]. Knowledge graphs have outstanding advantages in achieving semantic alignment and relational reasoning, such as the service-oriented digital twin framework constructed by Liu et al. (2024) that significantly improves the efficiency of infrastructure operation and maintenance, but its ability to model unstructured data relies on expert experience [3]. Although existing research provides an important theoretical foundation in fusion strategy and platform architecture, it still faces major challenges in deep semantic fusion, cross-domain scene adaptation and privacy-enhanced collaboration, and there is an urgent need to break through the bottleneck of the underlying technology of unified modeling and dynamic collaboration.

2.2. Research Progress on Co-optimization Strategies

Co-optimization strategies, as a key technical path for dynamic resource scheduling and cross-system collaboration in smart cities, have received extensive attention in recent years.Mazzetto (2024), in a study on digital twin integration, points out that multi-objective optimization algorithms show good decision-making efficiency in urban spatial scheduling, energy balancing, and risk control, especially in multivariate gaming scenarios with a strong reconciliation capability [4 Ge and Qin (2024) constructed a flood emergency model based on a generative urban twin system and proposed a distributed scheduling framework to achieve real-time response among urban modules, which improves the self-organization ability of the system but lacks the stability of handling unexpected large-scale tasks [5]. del Campo et al. (2024) introduced the Internet of Things (IoT) and Virtual Reality (VR) linkage mechanism in cross-domain collaborative research. attempted to construct a visual collaborative decision-making platform, but there are inference delays and model degradation problems in complex heterogeneous environments [6]. The current collaborative optimization strategies generally have the problems of insufficient adaptation to high-frequency data changes, incomplete collaboration mechanism of edge nodes, and ineffective balance between global optimal and local execution conflicts, and it is necessary to construct an intelligent scheduling framework with dynamic adaptability and robustness to improve the collaborative response capability and stability of complex urban systems in dynamic environments.

2.3. Practical Pain Points in Smart City Construction

Smart city projects have been implemented in many regions, but in actual operation, obvious shortcomings in cross-discipline collaboration have been exposed. Hangzhou "city brain" as an example, although the realization of traffic signal optimization and congestion warning, but in response to unexpected traffic events, the data interface between the departments is not unified, the response mechanism is fragmented, resulting in the disposal of efficiency constraints [7]. Singapore's "Smart Nation" program shows structural deficiencies in energy and environmental data linkage, and Hakimi et al. (2023) point out that in Singapore's digital twin infrastructure system, despite the deployment of a large-scale environmental sensing network, the lack of a unified data fusion standard has resulted in a serious phenomenon of data silos between different systems, affecting energy consumption and environmental protection. phenomenon is still serious, which affects the synchronized regulation of energy consumption prediction and pollution monitoring [8]. In addition, Sun and Ren (2024) emphasized in their study of multi-source heterogeneous fusion in an IoT environment that

ISSN: 2710-0588

real-time and precision are often not balanced in current smart city systems, especially in the linked scheduling of multidomain systems, where there are problems of delayed data updates and broken strategy feedback chains [9]. These cases reveal the deep-seated obstacles of the existing smart city technologies at the collaborative level, and verify the necessity and practical urgency of the cross-domain integration and optimization strategies proposed in this study in cracking the actual governance dilemma.

3. Smart City Cross-domain Data Fusion Key Technology

3.1. Methods for normalizing heterogeneous data from multiple sources

In order to effectively support the fusion of multi-domain data in smart cities, it is necessary to prioritize the resolution of the inconsistency of heterogeneous data at the structural, semantic and standard levels. A set of semantic ontology-driven dynamic standardization methodology system is designed, the core of which includes three modules: semantic ontology construction, cross-domain mapping rule generation, and standard data model adaptation. The semantic ontology is modeled by OWL (Web Ontology Language), and the high-level domain concepts and their attribute hierarchies are constructed for the domains of transportation, energy, security, etc. to unify the semantic labels. For structurally heterogeneous data (e.g., JSON, XML, CSV), a synergistic mechanism between semantic parser and structural mapper is introduced to achieve dynamic matching from structural to ontological nodes; through the multi-dimensional mapping rule base, the standardization of fields and the conversion of units are automatically completed, e.g., the temperature data is unified from °C to K, and the traffic speed is unified from km/h to m/s (Table 1). In order to improve the adaptability of the system, the dynamic query mechanism based on SPARQL and the data quality assessment module are designed to realize the adaptive standardization control of outliers and missing fields.

Table 1. Heterogeneous field mapping

Original field name	original format	Fields	Standard field name	standard unit	Mapping Rules in a Nutshell
temp_c	JSON	Energy Monitoring	temperature	K	K = temp_c + 273.15
speed_kmh	CSV	traffic control	speed	m/s	m/s = speed_kmh / 3.6
co2ppm	XML	Environmental Sense	co2_conc	ppm	direct mapping
power_w	JSON	Energy Dispatch	power	kW	kW = power_w / 1000

3.2. Real-time data fusion architecture design

In order to adapt to the high-frequency data generation and dynamic decision-making needs during the operation of the smart city, we design an "edge-cloud collaboration-driven real-time data fusion architecture", whose core lies in the low-latency fusion and high-frequency updating of cross-domain data through the layered collaboration between the data preprocessing capability of the edge side and the global computing resources of the cloud side. The architecture adopts a distributed event-driven model, with edge nodes deploying lightweight containers (e.g., K3s + MQTT Broker) that are responsible for local data filtering, standard conversion, and initial aggregation; the cloud builds a fusion scheduling engine as a microservice, based on Apache Kafka stream processing and Flink task flow, to standardize the data from different domains such as traffic, energy consumption, and security. unified modeling and global analysis [10]. A temporal indexing mechanism (based on GeoHash and time window

ISSN: 2710-0588

function) is introduced in the architecture for optimizing the efficiency of concurrent aggregation of dynamic data. Figure 1 shows the overall layered architecture design of the system, including the data flow path and processing logic between the sensing layer, edge layer, fusion layer and service layer. On this basis, the architecture retains interfaces to support asynchronous transmission, fault-tolerant recovery and data overload buffering to provide structural compatibility and deployment space for subsequent privacy control mechanisms.

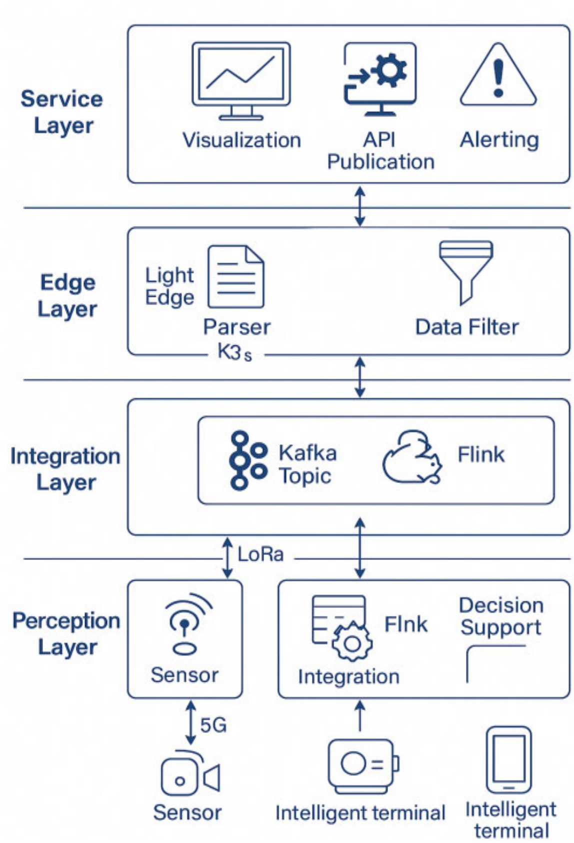

Figure 1. Real-time data fusion layered architecture diagram

3.3. Privacy protection and security mechanisms

In the process of constructing a multi-domain data fusion system for smart cities, guaranteeing the privacy and security of data when circulating between different departments and platforms is a prerequisite for the credible operation of the system. In this study, we design a data security sharing system that integrates the Differential Privacy (DP) mechanism with the Federated Learning (FL) framework, which takes into account the usability of city operation data and the privacy needs of the participating subjects. In the data local training phase, each edge node independently performs model updating based on its own data, and adopts parameter perturbation to introduce controllable noise (Laplace or Gaussian mechanism). Its differential privacy budget control formula is as follows:

$$M(D_1) \approx_{\varepsilon} M(D_2)$$

Where D1,D2 is a pair of neighboring datasets, M imposes a data processing algorithm or query mechanism with differential privacy mechanism, and is ε is the privacy budget, the smaller ε is the stronger the privacy protection. In order to achieve cross-domain collaborative modeling, the federated aggregation function is designed:

$$\theta_t = \sum_{i=1}^{n} \frac{w_i}{\sum w_i} \cdot \theta_t^i$$

ISSN: 2710-0588

Where θti denotes the local model parameter of the ith edge node at round t, and wi is its sample weight, which ensures that the model aggregation maintains fairness and generalization ability in a statistical sense. The Trusted Execution Environment (TEE) and Secure Multi-Party Computing (SMC) interfaces are also introduced to shield the risk of intermediate result leakage in the aggregation process.

4. Co-optimization Strategy Model Construction

4.1. Multi-objective collaborative optimization framework

Aiming at the complex coupling relationship between resource competition and spatio-temporal response of transportation, energy, security and other sub-systems in a smart city, a multi-objective collaborative optimization framework based on Multi-Agent System (MAS) is designed. The framework models each functional domain of the city as an autonomous intelligent body, defines its optimization objective function set F={f1,f2,...,fn}, and each intelligent body dynamically generates a local policy based on the local state si, resource constraints ri, and historical behaviors πi, and achieves global information synergy through a shared communication protocol. The overall optimization objective of the system is:

$$\min_{\pi_1,\ldots,\pi_n}\left(\sum_{i=1}^{n} w_i f_i(s_i,\pi_i)+\lambda\cdot C(\pi_1,\ldots,\pi_n)\right)$$

where wi denotes the objective weights, C(·) is the cost function of collaborative conflict, and λ is its regulation coefficient, which is used to balance the individual optimization with the global benefit of the system. A hierarchical control mechanism is introduced in the framework: edge intelligences perform local fast optimization, and the central coordinating intelligences perform global scheduling synchronization (Fig. 2). The structural design supports dynamic registration, autonomous negotiation and policy migration of intelligences, providing a unified decision logic and collaborative interface for adaptive optimization algorithm design.

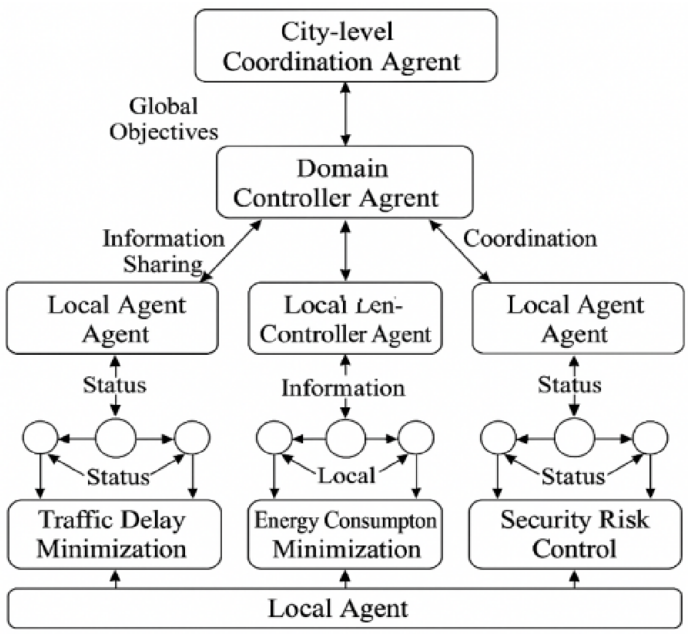

Figure 2. Multi-objective multi-intelligence body synergy architecture diagram

ISSN: 2710-0588

4.2. Dynamic Adaptation Algorithm Design

In order to cope with complex situations such as frequent state fluctuations and dynamic evolution of goal conflicts in smart city operation, this study designs a dynamic adaptive optimization algorithm based on Deep Reinforcement Learning (DRL) on the basis of multi-intelligent body collaborative framework. The core of the algorithm adopts the joint mechanism of state-action-value function (Q-Learning) and strategy gradient, so that each sub-system intelligence can adjust the local strategy according to the real-time sensing state and collaborate to reach the global optimization. The state space S consists of multidimensional indicators such as urban traffic flow density, load power, security alarm level, etc. The action space A corresponds to the resource allocation scheme, and the reinforcement learning objective function is:

$$\pi^* = \arg\max_{\pi} E_{s,a\sim\pi}\left[\sum_{t=0}^{T}\gamma^t R(s_t, a_t)\right]$$

where π∗ is the optimal policy, γ is the discount factor, and R(st,at) denotes the immediate synergy gain of the state-action pair at moment t. Considering multi-objective conflicts, this design introduces a weighted multi-objective reward function:

$$R(s,a) = \sum_{i=1}^{n} w_i \cdot r_i(s,a)$$

Where ri is the local reward of the ith domain (e.g., reduce energy consumption, reduce delay), and wi is the dynamic weight set by the policy layer. In order to enhance the algorithm's responsiveness to unexpected scenarios, a prioritized experience playback mechanism and a policy perturbation noise regulator are introduced to provide the system with good convergence and generalization capabilities in large-scale heterogeneous environments.

4.3. Simulation verification and parameter tuning

In the simulation validation phase, this study constructs a multidimensional dynamic environment integrating traffic flow and energy consumption data based on a digital twin platform in an eastern coastal city, and uses real collected high-frequency data (e.g., minute traffic flow, electricity load profile, meteorological parameters, etc.) to perform temporal simulation of multi-intelligent body co-optimization framework. The spatio-temporal aggregation of multi-source inputs is performed through the Flink stream processing pipeline to construct a unified state space S={s1,s2,...,sn}, on the basis of which the DRL-based multi-objective training is executed. Key parameters such as learning rate α, discount factor γ, and playback window length |M| are tuned by Bayesian optimization method, and the results show that the system converges optimally under the settings of learning rate α=0.0003, γ=0.95, and empirical playback window |M|=105bars. The simulation results, shown in Table 1, show that the cooperative strategy reduces the average traffic delay by 21.3% and the energy consumption per unit load by 16.8% during peak hours. In addition, in order to evaluate the real-time response capability and robustness of the strategy, a disturbance scenario (e.g., sudden traffic accidents, power consumption spikes) is introduced to simulate the test, and the average recovery time of the system is shortened from 87 seconds in the traditional scheduling to 54 seconds (Fig. 3), which verifies the adaptive capability and stability of the proposed algorithm in complex scenarios.

ISSN: 2710-0588

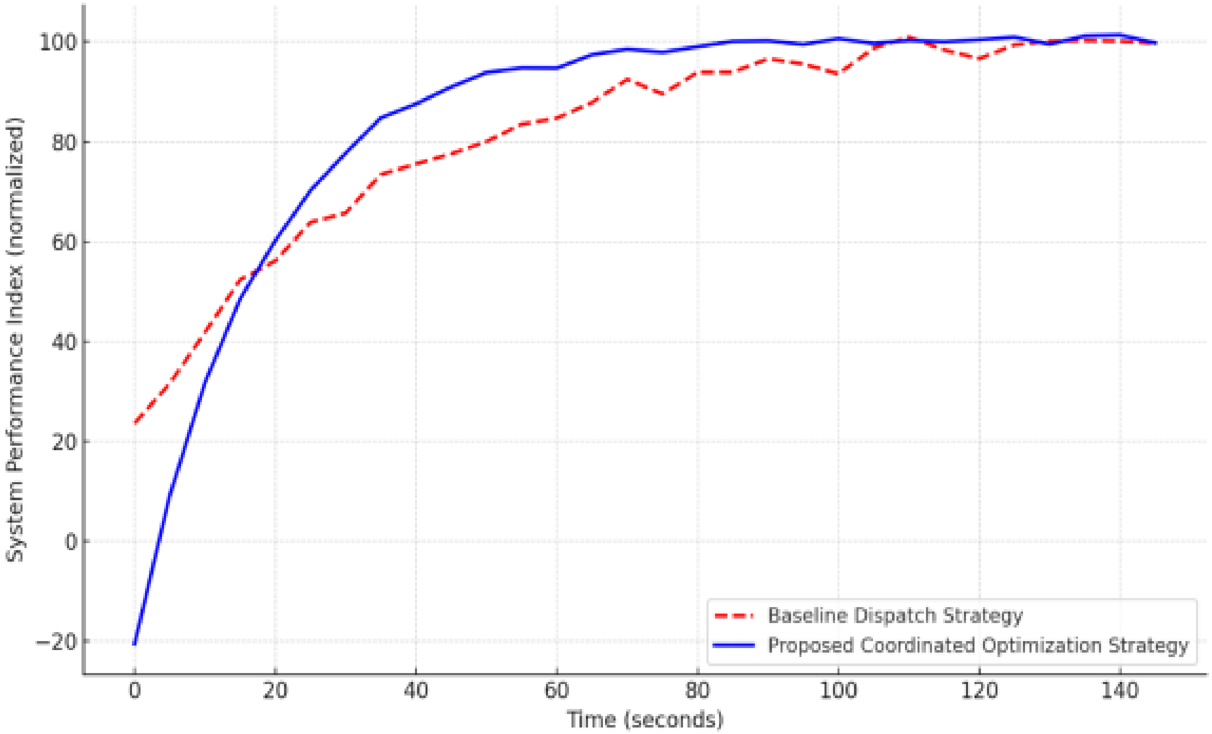

Figure 3. Timing curve of system recovery under sudden event perturbation

5. Smart City Management Software Collaborative Optimization Achievement Paths

5.1. Software Architecture Design

The smart city management software adopts the technology strategy of layered decoupling and containerized microservices in parallel in the architectural design, and builds a four-layer collaborative structure of "perception-data-model-application" (Figure 4). In the data layer, the data lake and time series database mechanism are integrated, taking into account the batch and streaming data access capability, and adopting a unified data access API to adapt to heterogeneous data sources, including IoT, satellite remote sensing, BIM, and other types of interfaces; in the model layer, the MAS intelligent body scheduling engine and the deep reinforcement learning inference module are integrated, and deployed in the Kubernetes cluster to realize dynamic expansion and elastic inference, and a parameter server (Parameter Server) is introduced to realize dynamic expansion and elastic inference. The model layer integrates the MAS intelligent body scheduling engine and deep reinforcement learning inference module deployed in the Kubernetes cluster to achieve dynamic scaling and elastic inference, and introduces the Parameter Server to optimize the multi-node asynchronous update of the policy model. The core scheduling engine of the algorithmic layer is based on event-driven architecture (EDA), using Apache Kafka and Flink to build a spatial-temporal event bus, realizing low-latency data flow routing control from the edge devices to the global scheduling. In order to ensure modular collaboration and lifecycle management, the architecture introduces a service-oriented distributed registry and policy configuration controller to support dynamic policy hot-plugging and multi-scenario reuse.

ISSN: 2710-0588

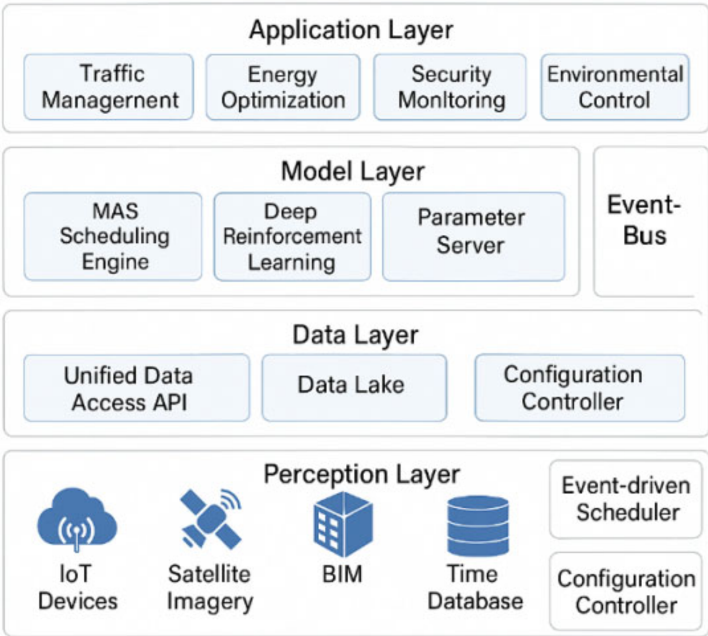

Figure 4. Software Architecture Diagram

5.2. Typical Application Scenario Realization

In the urban emergency response collaboration scenario, the system takes the event-driven mechanism as the core to build a "multi-departmental perception-determination-linkage-closed-loop feedback" response chain, with the perception layer accessing multi-source data nodes such as traffic police, firefighting, sanitation, etc., and real-time aggregation of emergency information based on the Flink event bus and GeoHash indexes, and the model layer The model layer schedules MAS intelligences for emergency task prioritization and resource redistribution. In order to guarantee the real-time scheduling link, the policy hash-based task delivery table (Table 2) is introduced, and the task hierarchical response policy is pre-configured and mapped and bound. In the regional energy-transportation linkage scheduling scenario, the system constructs a joint optimization model, and uses the traffic load forecast and the distribution network state as the state variables to form a joint state space $S_t = \{P_{load}^t, V_{node}^t, Q_{ev}^t\}$, and learns the interaction strategy between EV charging demand and spatial-temporal traffic flow through the DRL module, so as to realize the bidirectional coordination of load balancing and traffic peak avoidance.

Table 2. Configuration table for multilevel response strategy for emergency tasks

hierarchy	Trigger Event Type	Response window (seconds)	scheduling priority	Movement control resource set
I	Major traffic accidents, fires	30	your (honorific)	Traffic police, fire, medical
II	Moderate traffic congestion, facility failure	120	center	Roads, maintenance, energy regulation
III	Noise disturbance, water level fluctuation	300	lower (one's head)	Sanitation, drainage, environmental protection

ISSN: 2710-0588

5.3. Performance Evaluation and Optimization

Based on the aforementioned architecture and scenario deployment, the monthly operational datasets of transportation, energy consumption and security of a coastal city in 2023 are selected for comprehensive performance testing of the software system. The test dimensions cover response speed (Avg Latency), resource utilization (CPU/GPU Memory) and policy decision accuracy (Precision@Top-N). Under typical morning and evening peak event simulation, the average latency of optimized policy triggering to execution is controlled within 1.63 seconds, which is 43% shorter than the traditional modular scheduling scheme; the deployment test in Kubernetes heterogeneous nodes shows that the average CPU utilization rate of system containers is maintained at 58.6%, and the GPU load is no more than 72%, which ensures resource scheduling elasticity for algorithmic inference and data flow processing; at the same time, the introduction of unexpected scheduling tasks is used to ensure the flexibility of resource scheduling. In addition, the Top-N optimization recommendation mechanism is introduced in the burst scheduling task, and the task scheduling hit rate is increased to 91.2%. Figure 5 shows the comparison results of each performance index under multiple types of event scenarios. In response to the discovered problem of fluctuating delay of strategy cold-start, the Warm-Start mechanism and model pruning strategy are further introduced to effectively reduce the initial inference time of edge nodes and improve the consistency of the first response.

Figure 5. Radar chart comparing software performance in multiple scenarios

6. Empirical Studies and Case Studies

6.1. Experimental environment and data set

A prefecture-level city in Jiangsu Province is selected as the validation scenario, which is characterized by high population density, diversified industrial distribution, and perfect data

ISSN: 2710-0588

base, and has high representativeness and data accessibility. The dataset sources cover three categories: traffic flow data is provided by the intersection cameras of the city's Traffic Police Bureau in conjunction with the AutoNavi API, with a granularity of 5 minutes, covering 300+ road sections and 80 intersections; meteorological data is synchronized by the National Meteorological Bureau with the interface of the local Environmental Protection Bureau and contains indicators of temperature, humidity, wind pressure, and rainfall, with a 10-minute temporal resolution; and energy data comes from the city's electric power dispatch platform based on the load telemetry of distribution transformers, which is collected every 15 minutes. Energy consumption data comes from the municipal power dispatching platform, based on distribution transformer load telemetry, and is collected every 15 minutes. After the data are unified into the data center, the heterogeneous field standardization strategy is used to complete the semantic alignment and unit normalization process (Table 3), and the data cleaning module eliminates the abnormal time windows with a missing rate of more than 10%.

Table 3. Heterogeneous data semantic standard mapping

Original field name	data type	source system	Standard field name	unit (of measure)	mapping rule
veh_count	int	Road junction probe	traffic_volume	veh/min	direct mapping
temp_c	float	Meteorological platforms	temperature	K	K = temp_c + 273.15
power_load_w	float	Power Platform	power_load	kW	power_load = power_load_w /1000

6.2. Analysis of experimental results

Based on the multi-source data environment, the traditional baseline method and the cross-domain cooperative optimization system proposed in this study are deployed for comparative experiments, and the results show that the system in the data fusion phase of the average time consumption of structural matching and semantic alignment decreased by 34.6%, and the data timeliness is improved to 95.2% of the real-time coverage, which is significantly better than the traditional ETL + rule engine architecture. In terms of optimization effect, taking "traffic flow regulation in urban core area" and "staggered linkage of energy consumption in residential and industrial areas" as dual scenarios, the duration of traffic congestion is shortened by 18.7% and 21.4% in morning and evening peaks, respectively, and the fluctuation rate of energy consumption per unit area is reduced from 0.32% to 0.4%. The fluctuation rate of energy consumption per unit area is reduced from 0.32 to 0.19, and the stability index of urban operation is improved by 12.1% after the implementation of the strategy. Figure 6 shows the difference in the dynamic response of the system to the two key dimensions of transportation and energy under different strategies. In order to further quantify the efficiency improvement of fusion and scheduling, this study constructs the fusion efficiency ratio index $\eta_f = \frac{T_{baseline}}{T_{fused}}$, and when ηf>1.3, the system is identified as having engineering-level optimization potential, and the measured results satisfy this criterion in all five types of tasks (Table 4).

ISSN: 2710-0588

Table 4. Multi-scenario task fusion effectiveness ratio metrics assessment table

Scenario Mission Type	Tbaseline(s)	Tfused(s)	ηf	Optimization potential assessment
Traffic calming strategies loaded	4.31	2.87	1.50	your (honorific)
Energy Peak Regulation Strategy Generation	5.76	4.01	1.44	your (honorific)
Security anomaly warning issued	2.93	2.13	1.38	mid-to-high
Joint scheduling executive call	3.52	2.41	1.46	your (honorific)
Combined modeling of data from multiple sources	6.02	4.31	1.40	your (honorific)

7. Challenges and Future Prospects

In the process of implementation, smart city management system faces core technical difficulties such as unstable data quality from multiple sources, cross-domain semantic inconsistency and strong black-box modeling, especially in high-frequency scenarios, where data packet loss and outliers are frequent, severely restricting the robustness of fusion algorithms. At the model level, although the cooperative optimization strategy has systematic advantages, its scheduling logic is difficult to realize interpretable feedback paths in complex urban networks, which hinders its practical deployment in high-risk scenarios[11]. The system architecture also suffers from high interface coupling and weak closed-loop capability of the scheduling chain when expanding edge nodes and accessing heterogeneous modules. In the future, it is necessary to rely on the fusion mechanism of reinforcement learning and causal inference to build a cluster of intelligences that can be interpreted and have autonomy, and at the same time, safeguard the security of data sharing through the standardization of governmental data legislation and the trusted privacy computing system. In complex governance models such as carbon neutral and meta-cosmic cities, this technology system is expected to serve as the underlying operation platform to promote the paradigm shift of urban governance.

8. Conclusion

Focusing on the key issues of cross-domain data fusion and collaborative optimization in smart city management software, the article constructs a multi-source heterogeneous data standardization method, a real-time fusion architecture of edge-cloud collaboration, and a data security mechanism integrating federated learning and differential privacy, which effectively improves the accuracy and timeliness of data processing. In terms of optimization strategy, the multi-intelligent body system and deep reinforcement learning algorithm realize the adaptive and dynamic cooperation of resource scheduling, and verify the convergence and robustness of the model in high-frequency complex scenarios. At the practical level, the system realizes multi-scenario linked scheduling of transportation, energy, security, etc. in the real urban environment, which significantly improves the efficiency of urban operation and service responsiveness. The research results not only provide a systematic and deployable technical path for smart city governance, but also lay a theoretical foundation and engineering basis for the construction of highly resilient and adaptive urban intelligent systems in the future.

ISSN: 2710-0588

References

[1] Zou X, Yan Y, Hao X, et al. Deep learning for cross-domain data fusion in urban computing: Taxonomy, advances, and outlook[J]. Information Fusion, 2025, 113: 102606.

[2] Fadhel M A, Duhaim A M, Saihood A, et al. Comprehensive systematic review of information fusion methods in smart cities and urban environments[J]. Information Fusion, 2024: 102317.

[3] Li Z, He J, Fang X, et al. Overall framework of IoT platform in urban agglomeration-cross-city, cross-domain, cross-level, and one-network unified management architecture[C]//International Conference on Internet of Things and Machine Learning (IoTML 2023). SPIE, 2023, 12937: 239-247.

[4] Liu L, Zeng N, Liu Y, et al. Multi-domain data integration and management for enhancing service-oriented digital twin for infrastructure operation and maintenance[J]. Developments in the Built Environment, 2024, 18: 100475.

[5] Mazzetto S. A Review of Urban Digital Twins Integration, Challenges, and Future Directions in Smart City Development[J]. Sustainability, 2024, 16(19): 8337.

[6] Ge C, Qin S. A generative city digital twin system for flooding emergency management in smart city[C]//2024 29th international conference on automation and computing (ICAC). IEEE, 2024: 1-6.

[7] del Campo G, Saavedra E, Piovano L, et al. Virtual reality and internet of things based digital twin for smart city cross-domain interoperability[J]. Applied Sciences, 2024, 14(7): 2747.

[8] Anjum M, Shahab S, Khan M A, et al. A categorized information fusion model for reliable services delivery in smart cities[J]. Applied Soft Computing, 2024, 151: 111144.

[9] Hakimi O, Liu H, Abudayyeh O, et al. Data fusion for smart civil infrastructure management: A conceptual digital twin framework[J]. Buildings, 2023, 13(11): 2725.

[10] Sun R, Ren Y. A multi-source heterogeneous data fusion method for intelligent systems in the Internet of Things[J]. Intelligent Systems with Applications, 2024, 23: 200424.

[11] Chen R. The application of data mining in data analysis[C]. Proceedings of the International Conference on Mathematics, Modeling, and Computer Science (MMCS2022), 2023, 12625: 473-478. SPIE.