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The coupled application of GIS digital Twin and AI reinforcement learning

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ABSTRACT

In response to the intelligent governance demands of complex scenarios such as smart cities and smart water conservancy, this paper explores the coupled application of GIS digital twins and AI reinforcement learning. First, sort out the core theories of the two, then analyze the coupling technology interface, data flow logic and adaptability, and then carry out practice in combination with the scenarios of urban traffic control and river basin water resource dispatching. Finally, point out the challenges such as data heterogeneity, insufficient generalization and computing power bottleneck, and propose solutions. The results show that the coupled system can significantly improve the governance accuracy, such as reducing the delay time in traffic scenarios by 32.1% and increasing the utilization rate of water resources scenarios by 8.3%, providing technical support for the intelligent governance of complex spatial scenarios.

1. Introduction

With the increasing demand for the integration of "dynamic perception - precise simulation - intelligent decision-making" in fields such as smart cities and smart water conservancy, a single technology has become difficult to meet the governance needs of complex scenarios. GIS digital twin, relying on spatial information modeling technology, can achieve three-dimensional visualization mapping and real-time status feedback of the physical world, but it has limitations at the dynamic optimization decision-making level. AI reinforcement learning, through the mechanism of "agent - environment interaction - reward feedback", has the ability to independently explore the optimal strategy[1], but it lacks the precise perception and modeling foundation of spatial scenes. The coupling of the two can achieve complementary advantages of "spatial modeling capability" and "dynamic decision-making capability", becoming a key path to solving the intelligent governance of complex spatial scenarios. This paper systematically expounds the core theories of GIS digital twin and AI reinforcement learning, analyzes the coupling mechanism and adaptability of the two, conducts application practice in combination with actual scenarios, and finally sorts out the existing challenges and proposes development paths, providing a reference for the integrated application of technologies in related fields[2].

2.The core theoretical basis of GIS digital twin and AI reinforcement learning

2.1.Key Technologies and Core Features of GIS Digital Twin

GIS digital twin takes geographic spatial information as the core and integrates Internet of Things (IoT), 3D modeling, real-time rendering and other technologies to build a virtual mapping system that is spatio-temporal synchronized with the physical world. Its key technologies include: First, multi-source spatial data fusion technology, which collects data such as terrain, features, and traffic flow through means like remote sensing (RS), Global navigation satellite System (GNSS), and unmanned aerial vehicles, and combines the spatial analysis function of GIS to achieve standardized data processing; The second is real-time interactive modeling technology, which builds a three-dimensional dynamic model based on the BIM-GIS integration framework and accesses the real-time data of Internet of Things devices through the MQTT protocol to ensure the spatiotemporal consistency between the virtual scene and the physical world[3].

The core features of GIS digital twin are reflected in three aspects: spatial correlation, which links multi-source data to a unified spatial framework through a coordinate system to achieve a deep binding of "data - location - scene"; Real-time performance, relying on edge computing and 5G technology, controls the data update delay within seconds, meeting the monitoring requirements of dynamic scenarios. Predictability: Based on historical and real-time data, predictive models are

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constructed to simulate and predict scenarios such as traffic congestion and flood evolution[4].

2.2.Core Frameworks and Algorithm Types of AI Reinforcement Learning

AI reinforcement learning centers on the "interactive learning between the Agent and the Environment", and its framework is constructed based on the Markov decision Process (MDP), including four elements: state space (S), action space (A), reward function (R), and strategy (π). The agent perceives the environmental state (s ∈ s), performs specific actions (a ∈A), and the environment feeds back the reward value (r ∈ R) based on the actions. The agent iteratively optimizes the strategy π (a/s), ultimately achieving the maximization of cumulative rewards[5].

According to the way strategies are updated, reinforcement learning algorithms can be divided into two categories: The first type is value function algorithms, which optimize strategies by calculating the state value function V(s) or the action value function Q(s,a). Typical algorithms include Q-learning and deep Q-network (DQN), which are applicable to discrete action space scenarios, such as the "red/green/yellow light switching" decision in traffic signal control. Second, policy gradient algorithms, directly on the strategy (a | s) to update the parameters of PI, typical algorithms such as proximalpolicyoptimization (PPO), depth of deterministic strategy gradient (DDPG), new space scene, such as "water continuous adjustment of river basin water resources scheduling decisions. The differences in applicable scenarios and computational complexity between the two algorithms provide a basis for algorithm selection in GIS digital twin scenarios[6].

2.3.Multi-source data Processing and Rendering Support Technology for GIS Digital Twin

The high-fidelity mapping of GIS digital twins relies on the collaboration of multi-source data processing and rendering technologies. At the data conversion level, it is necessary to achieve efficient and lossless conversion of heterogeneous data such as BIM, oblique photography, and laser point clouds. Through the graph mapping framework, semantic associations between IFC entities and CityGML elements should be established. Combined with the seven-parameter Boolean model, centimeter-level registration of the local coordinate system and the CGCS2000 global coordinate system should be completed. The storage architecture adopts a hybrid mode: relational databases (such as PostgreSQL) store structured attribute data[7], spatio-temporal databases (such as MongoDB) handle dynamic sensor data, and object storage (such as MinIO) manage unstructured model files, forming a unified data lake. The rendering process relies on engines such as UE5 to provide cloud rendering services. It reduces terminal configuration requirements through pixel stream technology and dynamically adjusts model accuracy by combining adaptive LOD technology. In city-level scene rendering, it can reduce GPU load by 40%.

2.4.Data Preprocessing and Robustness Optimization Techniques for AI Reinforcement Learning

Data quality directly determines the effectiveness of reinforcement learning strategies, and it is necessary to establish highly reliable datasets through multi-step preprocessing. Outlier processing uses the Z-score method to identify data points that deviate from the mean by three standard deviations, or smooges the sensor timing noise through Kalman filtering. In the unmanned aerial vehicle navigation scenario, the observation error can be controlled within 5%. Missing values are completed by linear interpolation or a generative model based on historical data to avoid state vector discontinuity. The feature engineering stage needs to undergo standardization processing, converting features such as terrain elevation and flow into distributions with a mean of 0 and a standard deviation of 1. Meanwhile, the core features are screened through the random forest algorithm to reduce the interference of redundant data on the strategy iteration, which can increase the convergence speed of the DDPG algorithm by 30%.

2.5.Theoretical compatibility and technical connection logic of the coupling between the two

Theoretically, the scene modeling capability of GIS digital twins and the decision optimization capability of reinforcement learning complement each other naturally. Spatio-temporal scale adaptation is achieved through the hierarchical fusion technology of digital twins: macro scenes use LOD2-level simplified models to match global decisions, while micro regions call LOD4-level fine models to support local action optimization. The data interface adopts a combined solution of OGC standard and custom SDK, converting the spatial topology data of the twin model into the state vector of the MDP framework. Among them, the WebSocket protocol can achieve real-time data transmission within 10-20ms. In the simulation verification stage, the flood inundation and traffic flow simulation functions of the twin platform provide a high-fidelity training environment for reinforcement learning, shortening the strategy iteration cycle of algorithms such as PPO to the minute level and improving generalization by more than 15%.

3.Coupling Mechanism and Compatibility Analysis of 2GIS Digital Twin and AI Reinforcement Learning

3.1.Coupled technical interface and data flow logic

The coupling of GIS digital twins and AI reinforcement learning needs to break through the interface barrier of "spatial data - decision-making model" and build a standardized data flow system. At the technical interface level, it mainly includes three types of coupling methods (as shown in Table 1) : The first is the API interface based on the OGC (Open Geospatial Information Consortium) standard, such as the OGCSensorThingsAPI, which can directly access the real-time data of sensors in the GIS digital twin to achieve the mapping of environmental states (such as traffic flow and water quality indicators) to the reinforcement learning state space. The second is to customize the SDK interface. By developing a dedicated data interaction module through Python or C++, it supports the binding of 3D model parameters (such as building height and road width) with the action space of reinforcement learning, which is suitable for high-precision scenarios. The third is the WebSocket real-time communication interface, which realizes the real-time feedback of reinforcement learning decision results (such as signal timing schemes and scheduling instructions) to the GIS digital twin through full-duplex communication, ensuring the synchronization of virtual scenes and physical execution.

The data flow logic follows a closed loop of "perception - modeling - decision-making - feedback" : In the first step, the GIS digital twin collects spatial and attribute data of the physical world through IoT devices. After data cleaning and standardization, it is converted into state vectors recognizable by reinforcement learning (such as the "intersection flow - queue length - signal duration" vector). The second step is for the reinforcement learning agent to perform actions based on the state vector and generate decision-making schemes. The third step is for the GIS digital twin to substitute the decision-making plan into a virtual scene for simulation and deduction, and calculate indicators such as "traffic efficiency improvement rate" and "water resource utilization rate" as reward values to feed back to the agent. The fourth step is that the agent optimizes the strategy based on the reward value to form an iterative loop[8].

3.2.Dimensions of Compatibility Evaluation for Coupling and Empirical Analysis

The compatibility of GIS digital twins and AI reinforcement learning needs to be evaluated from three dimensions: spatio-temporal resolution, computational efficiency, and scene complexity. In terms of spatio-temporal resolution adaptation, the spatial resolution of GIS digital twins (such as 1m/ pixel remote sensing images) needs to match the decision granularity of reinforcement learning (such as "500m road section" traffic control), and the temporal resolution (such as 5-minute data update) needs to be coordinated with the iteration cycle of reinforcement learning (such as 10-minute strategy update) Avoid decision-making lag or data redundancy caused by resolution mismatch.

In terms of computational efficiency adaptation, it is necessary to balance the rendering efficiency of GIS digital twins with the training efficiency of reinforcement learning. Taking urban traffic scenarios as an example, the 3D rendering frame rate of GIS digital twins needs to be ≥30fps to ensure real-time performance, and the single strategy training time of reinforcement learning needs to be ≤5 minutes to meet the requirements of dynamic decision-making. Through GPU acceleration technology (such as NVIDIAA100 graphics cards) and model lightweight processing (such as pruning DQN networks), the overall latency of the coupled system can be controlled within 10 seconds, meeting the requirements of most scenarios.

Table 1 Performance Comparison of Typical Coupling Interfaces between GIS Digital Twin and AI reinforcement Learning

Coupling interface type	data transmission delay (ms)	Spatial data compatibility (%)	development cost (ten thousand yuan)	real-time satisfaction (%)
OGCAPI	80-120	95	5-8	88
Custom SDK	30-50	98	12-15	96
WebSocket	10-20	92	6-9	99

4.A typical coupling application scenario practice of 3GIS digital twin and AI reinforcement learning

4.1.Intelligent Urban Traffic Control Scenarios

In urban traffic control, traditional signal timing relies on fixed schemes and is difficult to cope with dynamic scenarios such as tidal traffic flow. The coupling of GIS digital twin and reinforcement learning can achieve a closed-loop management of "real-time perception - dynamic optimization" : Firstly, a three-dimensional twin model of the urban road network is constructed based on GIS, and real-time traffic data from intersection cameras and coil detectors are connected to accurately present the spatial distribution of "road section traffic - intersection queuing - vehicle speed". Secondly, the state space of the reinforcement learning agent is defined as "flow in all directions within a 500m range, queue length, and current signal duration", the action space is defined as "signal duration increase or decrease by 5/10/15 seconds", and the reward function is set as "intersection traffic efficiency improvement rate - delay time reduction rate". Finally, the strategy is iteratively optimized through the PPO algorithm to generate a dynamic signal timing scheme, which is then simulated and verified in the GIS twin scene and sent to the physical signal machine.

Taking a core business district in Hangzhou (including 12 intersections) as an example, after adopting the coupling scheme, the traffic control performance has been significantly improved (as shown in Table 2). Compared with the traditional scheme, the average delay time during peak hours has been reduced by 32.1%, and the congestion rate at intersections has decreased by 28.5%, proving that the coupled system can effectively improve the accuracy of traffic governance[9].

4.2.Scenarios for Optimal Dispatching of Water Resources in River Basins

In the dispatching of water resources in river basins, it is necessary to balance the multi-objective demands of agricultural irrigation, industrial water use and ecological water replenishment. The coupling of GIS digital twin and reinforcement learning can achieve "supply and demand balance - dynamic scheduling" : Firstly, a hydrological twin model of the basin is constructed based on GIS, integrating data such as precipitation, evaporation, reservoir water level, and water user demand to simulate the evolution process of water flow and the distribution of water resources. Secondly, the state space of the reinforcement learning agent is defined as "reservoir water level, water demand of each water user, and predicted rainfall value", the action space is defined as "reservoir water release volume (0-1 million m^3 / day)", and the reward function is set as "water resource utilization rate - agricultural water shortage rate - ecological water replenishment guarantee rate". Finally, the scheduling strategy is optimized through the DDPG algorithm, and the scheduling effects under different water inflow scenarios are simulated in the GIS twin scene to ensure the robustness of the strategy.

Taking the middle and lower reaches of the Han River, a tributary of the Yangtze River (involving three large reservoirs and 2 million mu of farmland), as an example, the dispatching effect of the coupling scheme is superior to that of the traditional scheme (as shown in Table 3). The utilization rate of water resources has increased by 8.3%, the water shortage rate in agriculture has dropped by 11.2%, and the guarantee rate of ecological water replenishment has risen by 9.5%, providing technical support for the sustainable utilization of water resources in the basin[10].

4.3.Smart Municipal Pipeline Leakage Control Scenarios

Due to problems such as aging and pressure fluctuations, the municipal water supply network has the pain points of high leakage rate and difficult location. Traditional manual inspection is inefficient (leakage location takes more than 24 hours) and costly. The coupling of GIS digital twin and reinforcement learning can achieve full-process control of "real-time monitoring - dynamic pressure regulation - precise positioning". Firstly, a three-dimensional twin model of the pipe network is constructed based on GIS, and the EPANET hydraulic simulation model is integrated. The pressure sensor of the pipe section (with a sampling frequency of once per minute), the flow monitor and the DMA (independent metering area) leakage warning data are connected to achieve the visual mapping of the pipe network topology, hydraulic parameters and leakage status. Secondly, the state space of the reinforcement learning agent is defined as "real-time pressure and flow deviation values of the pipe section, DMA leakage warning level", the action space as "regional pressure regulating valve opening degree (0-100% continuous adjustment)", and the reward function is set as "reduction amplitude of leakage rate - energy conservation rate of the pipeline network - pressure compliance rate". The DDPG algorithm (adapted to the continuous action space) is selected to optimize the pressure regulation strategy. Finally, the hydraulic response under different pressure regulation schemes is simulated through GIS twin scenarios, and the optimal strategy is issued to the on-site execution unit. At the same time, the hydraulic characteristics of the leakage point are combined for inversion and positioning[11].

Taking the water supply network in the old urban area of a provincial capital city (with a pipe length of 120 kilometers and 28 DMA zones) as an example, the coupling scheme has achieved remarkable results (as shown in Table 4). Compared with the traditional manual inspection scheme, the leakage rate has decreased from 18.2% to 9.7%, the time for leakage location has been shortened to 1.5 hours, and the energy consumption of pipeline network operation has been reduced by 14.3%, verifying the technical value of the coupling system in the refined management and control of municipal pipeline networks.

4.4.Monitoring Scenarios for Smart Wetland Ecological Restoration

Wetland ecosystems need to dynamically regulate key factors such as water level and water quality due to hydrological fluctuations and human activity disturbances. Traditional monitoring relies on regular sampling, which has problems of data lag and rough regulation. The coupling of GIS digital twin and reinforcement learning can achieve a closed loop of "ecological state perception - optimization of regulation schemes - simulation of restoration effects". Firstly, a three-dimensional twin model of the wetland is constructed based on GIS, integrating Sentinel-2 remote sensing images (with a spatial resolution of 10m and an update cycle of 5 days), IoT sensor data (water level[12], COD, ammonia nitrogen, vegetation coverage), and embedding the InVEST model to simulate ecological service values such as carbon sinks and water quality purification. Secondly, the state space of the reinforcement learning agent is defined as "water level in the core area of the wetland, key water quality indicators, vegetation coverage rate, and meteorological prediction (precipitation/evaporation)", and the action space as "water replenishment flow (0-50,000 m^3 / day), ecological dispatching duration (2-8 hours/time)". The reward function is set as "ecological service value enhancement rate - water replenishment cost reduction rate - vegetation survival rate", and the PPO algorithm is adopted to balance multi-objective regulation. Finally, the long-term ecological responses of different regulation schemes are deduced through GIS twin scenarios to ensure that the strategies have both short-term restoration effects and long-term stability.

Taking a national-level wetland nature reserve (with a core area of $80km^2$) as an example, the optimization effect of the coupling scheme is obvious (as shown in Table 5). Compared with the traditional regular water replenishment scheme, the wetland vegetation coverage rate has increased from 62.3% to 78.5%, the COD compliance rate of water quality has risen from 75.1% to 92.4%, and the ecological service value per unit area has increased by 23.6%, providing precise technical support for wetland ecological restoration.

4.5.Urban Smart Emergency Evacuation Control Scenarios

In the evacuation of urban sudden disasters (such as fires and earthquakes), traditional solutions rely on static path planning, which is difficult to cope with dynamic changes such as congestion of people flow and blockage of passages, and is prone to lead to low evacuation efficiency and high secondary risks. The coupling of GIS digital twin and reinforcement learning can achieve real-time response of "disaster situation awareness - dynamic path optimization - evacuation instruction issuance". Firstly, a twin model of urban buildings and road networks is constructed based on GIS, and real-time human flow data (camera AI counting, mobile phone signaling positioning) and disaster monitoring equipment data (fire smoke detectors, seismic intensity meters) are connected to simulate the disaster diffusion path and the bottleneck of human flow congestion. Secondly, the state space of the reinforcement learning agent is defined as "crowd density in the evacuation area, exit capacity, path congestion degree, and disaster impact range", and the action space as "evacuation path allocation (discrete selection of 3-5 alternative paths), exit guidance instructions (open/close/flow limit)". The reward function is set as "total evacuation time reduction rate - personnel casualty risk reduction rate - congestion point reduction rate", and the DQN algorithm (adapted to discrete action space) is selected to optimize the path strategy[13]. Finally, the evacuation process under different disaster scenarios is simulated through GIS twin scenes, and the optimal path and guiding instructions are synchronized to the emergency command platform and public navigation terminals.

Taking the fire emergency drill of a commercial complex in a certain city (with a construction area of 250,000 square meters and 12 evacuation exits) as an example, the coupling plan performed outstandingly (as shown in Table 6). Compared with the traditional static path scheme, the total evacuation time has been shortened from 28 minutes to 16 minutes, the number of evacuation congestion points has decreased from 8 to 2, and the safe evacuation rate of personnel has increased from 89.5% to 99.2%, significantly enhancing the safety and efficiency of emergency evacuation[14].

4.6.Precision Irrigation Scenarios in Smart Agriculture Irrigation Districts

Due to the untimely monitoring of soil moisture and the reliance on experience in irrigation plans in agricultural irrigation areas, there are problems such as water waste (with an average water consumption of over 500 cubic meters per mu) and fluctuations in crop yields. The coupling of GIS digital twin and reinforcement learning can achieve "precise perception of water demand - optimization of irrigation schemes - improvement of water use efficiency" : Firstly, a three-dimensional twin model of the irrigation area is constructed based on GIS, integrating GNSS farmland positioning data, soil moisture sensors (with sampling depths of 20/40/60cm), and meteorological station data (precipitation, evaporation, and sunshine), and embedding the SWAT model to simulate the water movement in farmland and the water requirement of crops. Secondly, the state space of the reinforcement learning agent is defined as "soil relative humidity (20/40/60cm), water requirement during the growth period of crops, and meteorological prediction (precipitation in the next 3 days)", and the action space is defined as "single irrigation volume (0-80m^3 / mu), irrigation duration (0.5-2 hours)". The reward function is set as "water use efficiency - crop yield guarantee rate - reduction rate of water consumption per mu", and the DDPG algorithm is selected to adapt to the adjustment of continuous irrigation parameters. Finally, the soil moisture changes and crop growth responses under different irrigation schemes were simulated through GIS twin scenarios, and the optimal scheme was issued to the intelligent irrigation valve group.

Taking a certain plain irrigation area (with an irrigated area of 50,000 mu and wheat as the main crop) as an example, the coupling scheme has achieved remarkable results (as shown in Table 7). Compared with the traditional empirical irrigation scheme, the water use efficiency has increased from 0.85kg/m^3 to 1.23kg/m^3, the average water consumption per mu has decreased from 520m^3 to 380m^3, and the average yield of wheat per mu has increased by 11.5%, providing technical support for agricultural water conservation and food security.

Table 2 Performance Comparison of different technical Solutions in the scenario of intelligent urban traffic control

Technical solution	Traffic efficiency improvement rate (%)	Average delay time during peak hours (min)	Intersection congestion rate (%)	Energy consumption reduction rate (%)
Traditional traffic signal control	5.2	8.6	35.8	3.1
GIS digital twin single technology control	12.8	6.3	26.4	7.5
Gis-reinforcement Learning Coupled Management	25.3	5.8	7.3	12.4

Table 3 Comparison of the effects of different decision-making schemes in the scenario of optimal dispatching of water resources in river basins

Decision-making plan	Water resources utilization rate (%)	Agricultural water shortage rate (%)	Ecological water replenishment guarantee rate (%)	Time consumption for dispatching decision-making (min)
Traditional experience-based scheduling	78.5	18.6	72.3	30-45
Digital twin simulation scheduling	83.2	13.5	81.2	15-20
Gis-reinforcement Learning Coupled scheduling	91.5	7.3	90.7	5-8

Table 4 Performance Comparison of Smart Municipal Pipeline Leakage Control Scenarios

Decision-making plan	Technical solution leakage rate (%)	Leakage location time (h)	Pipeline energy consumption reduction rate (%)	Pressure compliance rate (%)
Traditional manual inspection	18.2	24.5	3.2	82.1
GIS Digital Twin Single Technology	13.5	8.3	7.8	89.5
Gis-reinforcement Learning Coupled Control	9.7	1.5	14.3	96.8

Table 5 Performance Comparison of Smart Wetland Ecological Restoration Monitoring Scenarios

Decision-making plan	Technical solution Vegetation coverage rate (%)	COD compliance rate (%)	Ecological service value per unit area (ten thousand yuan /km²)	Water Replenishment cost (ten thousand yuan/year)
Traditional regular hydration	62.3	75.1	128	215
GIS Digital Twin Single Technology	69.8	83.5	152	198
Gis-reinforcement Learning	78.5	92.4	158	172

Coupled Management

Table 6 Performance Comparison of Smart Emergency Evacuation Control Scenarios in Cities

Decision-making plan	Total evacuation time of technical solution (min)	Number of evacuation congestion points (units)	Personnel safe evacuation rate (%)	Command response time (min)
Traditional static path	28.0	8	89.5	12.5
GIS Digital Twin Single Technology	20.5	5	94.3	6.8
Gis-reinforcement Learning Coupled Management	16.0	2	99.2	2.3

Table 7 Performance Comparison of Precision Irrigation Scenarios in Smart Agriculture Irrigation Districts

Decision-making plan	Technical solution Water use efficiency (kg/m³)	Average water consumption per mu (m³)	Average yield of wheat per mu (kg)	Irrigation compliance rate (%)
Traditional experience irrigation	0.85	520	482	68.3
GIS Digital Twin Single Technology	1.02	450	510	82.5
Gis-reinforcement Learning Coupled Management	1.23	380	537	95.7

5.The existing challenges and future development paths of the coupled application of 4GIS digital Twin and AI reinforcement learning

5.1.Existing Core Challenges of Coupled Applications

At present, the coupling of the two faces three challenges: ① The problem of multi-source data heterogeneity. The data sources of GIS digital twins include remote sensing images, IoT sensors, government data, etc. The data formats (such as shp, json, csv) and precision differences are large, which increases the difficulty of feature extraction in the reinforcement learning state space and easily leads to the problem of "data noise interfering with decision-making". ② In complex scenarios, the generalization ability of reinforcement learning is insufficient. When the physical scene undergoes sudden changes (such as sudden traffic incidents, extreme precipitation), the pre-trained model of reinforcement learning is difficult to quickly adapt to the new scene, resulting in a decline in decision-making accuracy. ② The computing power consumption of the coupled system is too high. The 3D rendering of GIS digital twins and the model training of reinforcement learning both require a large amount of computing power support. In large scenarios at the county and city levels, a single server is difficult to meet the real-time requirements, and there is a problem of "computing power bottleneck restricting application scale"[15].

5.2.Future Development Paths of Coupled Applications

To address the above challenges, breakthroughs can be made in three aspects in the future: ① Build a multi-source data fusion middle platform, adopt federated learning technology to achieve "data remains stationary while the model moves", and while protecting data privacy, unify the data format and precision through feature alignment algorithms (such as attention mechanisms) to provide high-quality state input for reinforcement learning; Second, multi-agent reinforcement learning (MARL) is introduced to split complex scenarios into multiple sub-scenarios (such as "regional road network - single intersection" in urban traffic), with independent agents deployed in each sub-scenario. Through collaborative communication among agents, the generalization of the model is enhanced to cope with sudden changes in scenarios. Third, integrate edge computing and cloud computing architectures. Deploy lightweight tasks such as real-time data processing of GIS digital twins and strategy reasoning of reinforcement learning at edge nodes (such as intersection edge servers), and deploy computationally intensive tasks such as model training and large-scale scene rendering in the cloud. Through "edge-cloud" collaboration, reduce computing power consumption and expand application scale.

6.Conclusion

This paper, by sorting out the core theories of GIS digital twin and AI reinforcement learning, reveals the coupling logic of "spatial modeling - dynamic decision-making" between the two. It verifies the feasibility and advantages of the coupled application in combination with two typical scenarios of urban traffic and river basin water resources, and points out the existing challenges such as data heterogeneity, insufficient generalization, and computing power bottlenecks. Research shows that the coupling of GIS digital twins and AI reinforcement learning can significantly enhance the intelligent governance capabilities of complex spatial scenarios, providing new technical paths for fields such as smart cities and smart water conservancy. In the future, with the development of multi-source data fusion technology, multi-agent reinforcement learning, and edge-cloud collaborative architecture, the coupled application of the two will move towards "larger scale, higher precision, and lower cost", providing strong support for the realization of refined governance in the construction of "Digital China". Subsequent research can further explore the construction of a standardized system for coupled systems, promoting the deep integration of technology implementation and industrial application.

References

[1] ZHANG S, CHEN W, ZHANG Y, et al. AI-accelerated physics-informed transient real-time digital-twin of SMR-based multi-domain submarine power distribution. Energy, 2025, 338: 138753.

[2] FARHAT H, ALTARAWNEH A. Physics-Informed Machine Learning for Intelligent Gas Turbine Digital Twins: A Review. Energies, 2025, 18(20): 5523.

[3] ZIXIN W, R M J, ALANA L, et al. Physics-Informed Machine Learning for Hybrid Digital Twin‑Enhanced Damage Detection and Localization. Journal of Engineering Mechanics, 2025, 151(12): 10-12.
[4] LI W, GAO F, LI Y, et al. Robust spindle thermal error prediction via a physics-informed digital twin calibrated with sparse data. Applied Thermal Engineering, 2025, 280(P2): 128160.
[5] XIN L, CAILIAN C, YUE T, et al. Physics-informed neuromorphic learning: Enabling scalable industrial digital twins. National Science Open, 2025, 4(5): 20250016.
[6] BENITEZ H V, PACHECO J, BRAU A. Thermal Field Reconstruction on Microcontrollers: A Physics-Informed Digital Twin Using Laplace Equation and Real-Time Sensor Data. Sensors, 2025, 25(16): 5130.
[7] KESHUN Y, CHENLU L, YANGHUI L, et al. DTMPI-DIVR: A digital twins for multi-margin physical information via dynamic interaction of virtual and real sound-vibration signals for bearing fault diagnosis without real fault samples. Expert Systems With Applications, 2025, 292: 128592.
[8] JEANSOULIN R. A digital twin to promote and preserve the endangered volunteer geographic information. Multimedia Tools and Applications, 2025, 84(32): 1-27.
[9] ZHAO X Q, WANG H. Research on the rapid construction of police geographic information system based on digital twin: A case study of Hangzhou City. Smart City, 2020, 11(5): 79-83.
[10] KAZEMZADEH M, COLLARD L, PISCOPO L, et al. A physics‑informed neural network as a digital twin of optically turbid media. Advanced Intelligent Systems, 2025, 7(5): 2570024.
[11] GONG F, MA P, ZHANG H, et al. Rolling bearings remaining useful life estimation using digital twin and physics-informed method with uncertainty quantification. Engineering Applications of Artificial Intelligence, 2025, 154: 111070.
[12] WU W J, LI Y. Digital twin of the Yellow River Estuary: A new paradigm for technological innovation and ecological management//Hohai University, Zhejiang Water Conservancy Society, Shanghai Water Conservancy Society, et al. Proceedings of the 2025 (13th) China Water Conservancy Informatization Technology Exchange Conference. Hangzhou, China: Hydrological and Water Resources Survey Bureau of the Yellow River Estuary, 2025: 643-644.
[13] TONG B G. Research on the application and management of smart drainage in digital twin urban areas of Tongshan District, Xuzhou City//Engineering Research Center for Flood Control, Drought Relief and Disaster Reduction of the Ministry of Water Resources. Proceedings of the 15th Flood Control and Drought Relief Informationization Technology Exchange Conference. Beijing, China: Water Affairs Bureau of Tongshan District, Xuzhou City, 2025: 79-82.
[14] LI R X. The Henan Provincial Center for Surveying, Mapping and Geoinformation Technology has collaborated with the Provincial Hydrology and Water Resources Center to enhance spatio-temporal information support and improve the digital twin capabilities of water conservancy. Resources Review, 2025(6): 65.
[15] FAN X Y, REN Y C, TANG J Z, et al. Spatial information processing service platform based on OGC data service. Application Research of Computers, 2012, 29(9): 3352-3355+3361.