Construction of a Smart City Infrastructure Dynamic Monitoring and Emergency Dispatch Model Supported by High-Precision Spatiotemporal Big Data

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ABSTRACT The increasing integration of IoT sensors, fiber-optic sensing and wireless communication links into urban architecture has made smart city infrastructure more vulnerable to disruptions as these complex, dynamic operating environments grow increasingly diverse with connectivity. Traditional static management frameworks cannot solve the problem of real-time perception and comprehensive planning of cross-system hazards. This paper proposes a dynamic monitoring and emergency dispatch model based on high-precision spatio-temporal big data. A data twin view of an integrated system based on heterogeneous data in the form of IoT sensing, remote sensing, GIS, and social sensing is established with a common spatiotemporal reference point. Accordingly, multi-layer complex networks are used to describe infrastructure dependencies, and spatiotemporal graph convolutional networks are integrated to obtain dynamic risk propagation simulations. In addition, a better non-dominated sorting genetic algorithm is adopted for multi-objective adaptive emergency resource scheduling. The results show that the model's anomaly identification accuracy is 95.3, risk propagation prediction accuracy is 88.7, and only the time to generate the schedule is 4.2 seconds. The proposed data fusion and scheduling logic is consistent with smart-city systems that rely on wireless sensing, remote sensing and communication infrastructure.

INDEX TERMS smart city infrastructure,spatiotemporal big data,emergency dispatch,risk propagation,urban sensing

I. INTRODUCTION

THE rapid pace of global urbanization and the pervasiveness of digital technologies are steering urban infrastructure toward greater complexity, especially as functional membranes and sensor-embedded fibers become integral to the interconnectedness and dynamism of modern smart systems. The formation of smart city concepts depends on the comprehensive knowledge and intelligent control of the operational conditions of the most important infrastructure elements of the city, such as transportation, energy, water supply, and communication networks. Nevertheless, because the physical linkages and functional interrelationships between infrastructure subsystems are becoming more intimate, they are exposed to cascading risks in dealing with natural disasters, accidental events (made by humans), or technical problems.

A multi-source heterogeneous data fusion architecture, which is inspired by a common spatiotemporal benchmark, is designed in this paper. It builds a digital twin representation of infrastructure functioning updated with a minute-by-minute using feature extraction and deep learning methods to address the problem of full dynamic look, and to solve the difficulty of comprehensive dynamic perception. A multi-layer spatiotemporal graph convolutional network is used to plan the intricate relationships among infrastructure items so that dynamic modeling of risk propagation trajectories and identification of the key vulnerable nodes are accomplished. This enhanced non-dominated sorting genetic algorithm, built upon a multi-objective adaptive emergency dispatch model, dynamically optimizes the allocation of critical relief materials and high-performance fiber resources to ensure efficient response and system resilience across the entire emergency management network.

The structure of this paper is as follows: it reviews the research progress related to smart city infrastructure and points out the existing shortcomings; it elaborates on the proposed three-layer model methodology; it verifies the model performance and discusses its advantages through

simulation experiments, historical case review, and composite disaster scenario testing; and it summarizes the whole paper and looks forward to future research directions.

II. RELATED WORK

As the pace of global urbanization accelerates and digital technologies are integrated into urban environments, the nature of smart city infrastructure has changed, becoming extremely complex, interconnected, and continuously functioning networks. Omelyanenko and Omelianenko [1] demonstrated that the presented method will be able to give systematic guidance based on the creation of innovative Hromadas. Alnahari and Ariaratnam [2] discussed the possibility of using blockchain technology as a decentralized, immutable, distributed registry in smart city infrastructure. Träskman's [3] study concluded that smart city activities are essentially an organizational process and a reconfiguration process that combines new technologies with old infrastructure. Wang et al. [4] conducted a comprehensive study on the standardization progress of urban infrastructure in the context of smart cities. Hromada et al. [5] emphasized combining physical security, network security, information security and other aspects to measure the anti-interference and recovery capabilities of infrastructure systems by integrating multi-source data and formulating evaluation indicators and models.

The sustainability of smart city infrastructure projects is not only related to technology and economy, but also includes important social dimensions. Li et al. [6] conducted a critical review of relevant research on public participation in the social sustainability evaluation of smart city infrastructure in the context of big data. Haque [7] conducted a quantitative assessment of IoT integration for reducing the vulnerability of urban infrastructure. Ghanem et al. [8] proposed an Internet of Things (IoT)-based framework specifically designed to address lane detection problems affected by artificial colored light in tunnels and highways. Mohammed [9] explored how to protect hundreds of millions of IoT devices from intrusion and ensure the cyberphysical security of critical smart infrastructure. Pandey [10] explored how cloud computing can serve as an enabling technology to support AI-enhanced smart city infrastructure management. Existing research has made significant progress in the constituent elements, key technologies and local optimization of smart city infrastructure, but has failed to achieve real-time perception, collaborative analysis and emergency dispatch linkage of cross-system risks under a unified, data-driven framework. This paper promotes the transformation of urban infrastructure management from "static planning and passive response" to "dynamic monitoring and proactive adaptation" by integrating multi-source heterogeneous data, characterizing the spatiotemporal dynamic behavior of infrastructure systems, and developing intelligent scheduling algorithms.

III. METHODS

A. MULTI-SOURCE HETEROGENEOUS DATA FUSION AND DYNAMIC SENSING

The foundation of the model lies in the high-precision, real-time perception of the operational status of urban infrastructure. This layer aims to address the challenges of data fusion caused by diverse data sources, different formats, and varying spatiotemporal scales. The main data sources include:

(1) Internet of Things sensor data: from sensors deployed in key facilities such as roads, bridges, pipelines, and substations, providing high-frequency time-series data of physical parameters such as vibration, pressure, flow, and voltage.

(2) Remote sensing and geographic information system data: including high-resolution satellite images, UAV aerial photography data, digital elevation models, etc., providing macroscopic spatial information such as surface deformation, water body changes, and building density.

(3) Urban operation management data: such as traffic flow monitoring data, power supply network load data, and water supply network pressure data, reflecting the system-level operational status of infrastructure.

(4) Social perception data: such as social media check-ins, public opinion information, and mobile signaling data, indirectly reflecting population activities and infrastructure usage intensity [11].

In order to overcome the issue of multi-source data fusion, this paper develops a data fusion framework on a combined spatiotemporal benchmark. The first comes in the form of spatial interpolation (including Kriging interpolation) and temporal alignment algorithms to bring data of various sources onto the same spatiotemporal grid. Second, where there is a variety of data, feature engineering techniques are specifically utilized to derive the main indicators that are used to describe the state of infrastructure health. To illustrate one example, frequency domain features are obtained to detect structural anomalies of bridge sensor data; congestion indices and average vehicle speed are obtained regarding traffic flow data. Lastly, so-called multisource indicators are merged with Kalman filtering or encoder-decoder architectures in deep learning to create a holograph, dynamic digital twin view of operational status of the infrastructure. This perception is updated at the minute-level or even the second-level frequencies, and this provides a high quality data base on which further risk analysis is done.

B. INFRASTRUCTURE DEPENDENCY MODELING AND RISK SIMULATION

Once one has dynamic sensing data, then the real work is to comprehend the behavior of interacting information in and between the infrastructure systems, and the evaluation of the routes and spread of dangers. The complex network theory is used in this layer to abstract the urban infrastructure into a multi-layered network. Each layer is a kind of infrastructure subsystem (including power grid, transportation network, and water supply network), network node is a particular

facility (including substations, intersections, and pumping stations), and edges are either physical (including cables, roads, and pipelines) or functional (including traffic lights that require power supply).

The weights of network edges no longer rely on static expert knowledge, but are dynamically calculated based on historical operating data, real-time monitoring data, and physical models, thereby greatly reducing subjectivity. The weights are comprehensively assigned using a combination of the analytic hierarchy process (AHP) and the entropy weighting method, and cross-validated using historical failure data to ensure their rationality. Furthermore, to address the uncertainty of the weights, a Bayesian network is introduced for probabilistic modeling. In risk simulation, Monte Carlo sampling is used to generate multiple possible scenarios to assess the confidence interval of risk propagation. It is based on this that a spatiotemporal graph convolutional network model is created. The model is capable of both measuring the spatiotemporal variation of node attributes (e.g., the time series of load of electricity) and network topology (e.g., the relationship of connection between nodes), thus, providing the correct modeling of the dynamic behavior of the infrastructure system. In case the perception layer identifies an action that is abnormal in one or more nodes (pressure drops abruptly or an abnormal flow), the model may be used to simulate the propagation of the abnormal state through the weighted network, forecast the extent and degree by which the abnormal nodes are impacted, as well as the loss of system functions, and obtain early warning on the risks. The vulnerability assessment is achieved by identifying the key hub nodes in the network (by computing the centrality index of the network nodes i.e. betweenness centrality and eigenvector centrality) which will cause a massive effect on the overall system upon failure.

C. MULTI-OBJECTIVE ADAPTIVE EMERGENCY DISPATCH

The ultimate goal of dynamic monitoring and risk simulation is to guide scientific emergency response. This paper focuses on emergency response scenarios, and its objective is to generate the optimal emergency resource allocation plan under conditions of limited resources and tight time constraints. This is a typical multi-objective optimization problem, and its objective function usually includes:

(1) minimizing emergency response time: ensuring that rescue forces (such as maintenance teams and emergency power supply vehicles) reach the fault point as quickly as possible.

(2) maximizing resource utilization efficiency: rationally allocating manpower, materials and equipment, and avoiding resource waste or local surplus.

(3) minimizing social impact: prioritizing the restoration of the functions of key infrastructure that have the greatest impact on people's livelihood and the economy.

This study uses an improved non-dominated sorting genetic algorithm to solve this multi-objective optimization problem. The algorithm encodes potential scheduling schemes as chromosomes and continuously evolves the population through selection, crossover, mutation and other operations, and finally obtains a set of Pareto optimal solutions, that is, no one scheme is better than another in all objectives. Decision-makers can select the most suitable scheme from the Pareto frontier according to the current priority strategy (such as prioritizing people's livelihood in the early stage of disaster). Furthermore, the model explicitly considers the logical constraints of resource availability. Resources (such as high-performance fiber optic cables, maintenance equipment, and rescue personnel) may be consumed or damaged during a disaster, and their inventory information is dynamically updated in real time through the perception layer. The scheduling scheme must meet the resource availability limit to avoid allocating depleted resources. Resource constraints are incorporated into the model during the optimization process to ensure the feasibility of the scheduling scheme. More importantly, the scheduling model is adaptive. It will receive updated information from the perception layer and risk simulation layer in real time. Once a new fault point or risk propagation path is detected, the optimization algorithm will immediately recalculate and dynamically adjust the scheduling scheme to ensure that the decision is always based on the latest situation information.

IV. RESULTS AND DISCUSSION

A. VALIDATION OF THE BASIC PERFORMANCE OF THE MODEL BASED ON SIMULATED DATA

In order to properly assess performance of the main components of the model under a controlled setup, simulated small urban area was built. There are 500 power nodes (substations and distribution centres), 800 traffic nodes (highway intersections), and 300 water supply nodes (water plants and pumping stations, in general). A set of interdependencies among these nodes was pre-determined basing on geographical proximity and functional dependence. Such as a traffic light node relies on a power node, a water pumping station node relies on and through roads on traffic nodes to be available to maintain the station. The simulation experiments were conducted using Python 3.9. A complex network model was constructed using the NetworkX library, and discrete event simulations were performed using SimPy. Random cascading failures were modeled using the CASCADE method based on a load-capacity model. This method states that when a node or edge fails, its load is redistributed to neighboring nodes in a certain proportion. If the load of a neighboring node exceeds its capacity, subsequent failures are triggered. To test the abovementioned model in terms of anomaly detection, risk, and generating schedules, 100 scenarios representing different types of failure events were randomly produced in this simulation environment, such as failures of a single node at random, failures of multiple neighboring nodes caused by localized disasters (e.g., simulated explosions or fires), as well as a random cascade of failures. Table 1 demonstrates the crude performance test

outcomes of the model with the assistance of simulated data.

TABLE 1. Basic Performance Test Results of the Model

Performance metrics	Average	Standard deviation	Optimal value	Worst value
Anomaly detection accuracy (%)	95.3	2.1	98.5	90.1
Risk propagation prediction accuracy (%)	88.7	3.5	94.2	81.0
Scheduling plan generation time (seconds)	4.2	1.3	1.8	7.5
Scheduling scheme response time reduction rate(%)	27.9	5.6	38.4	18.2

Note: The response time reduction rate of the scheduling scheme is the average improvement rate relative to the traditional shortest path scheduling method.

As shown in Table 1, the model performs exceptionally well in anomaly identification, achieving an average accuracy of 95.3%, demonstrating the effectiveness of multi-source data fusion and feature extraction. This superior performance is primarily attributed to the effectiveness of the multi-source data fusion strategy. Specifically, when a power node experiences a sudden voltage drop, power sensor data alone may be insufficient to distinguish between internal faults and external influences. However, the model simultaneously analyzes traffic monitoring data (whether there is congestion due to traffic light malfunctions) and social media data (whether users have reported power outages in the area). Through cross-validation of this information, the probability of false alarms and missed alarms is significantly reduced. The average accuracy of risk propagation prediction is 88.7%, indicating that the constructed complex network model can effectively simulate the cascading effects of faults. However, some errors still exist, stemming from insufficiently accurate estimation of dependency weights. In terms of computational efficiency, the average generation time of the scheduling scheme is only 4.2 seconds, meeting the real-time requirements of emergency response. Compared with the baseline method, the scheduling scheme generated by this model can shorten the emergency response time by an average of 27.9%, significantly improving rescue efficiency.

B. COMPARATIVE ANALYSIS BASED ON HISTORICAL CASE DATA

To further evaluate the model's potential in real-world scenarios, this study selected a historical event in a city caused by heavy rainfall, resulting in localized flooding and traffic disruption, as a case study. Using publicly available data and some simulated data, the state of the infrastructure network at the time of the event was reconstructed, and the model and the city's actual emergency response plan were retrospectively compared. The city's actual approach was based on a traditional method of static emergency plans and manual decision-making, which allocated resources according to a pre-defined priority list and fixed scheduling paths, lacking the ability to respond to real-time dynamic information. The results are shown in Table 2:

The contrast in decision latencies was significant. The entire process from when the monitoring system sends out a warning signal to the command center's confirmation of the alarm, consultation and assessment of the emergency situation, and the final decision to dispatch a rescue team takes about 25 minutes. However, when the perception layer is able to verify that the water level exceeds the threshold through water accumulation sensors and video analysis, the model can automatically perform risk simulation and generate a preliminary dispatch plan within 3 minutes, an almost real-time decision response. This 22-minute gap is critical in the race against time for emergency response. In terms of scheduling efficiency, the model's solution will be more efficient than the real solution in terms of rescue arrival time, reconstruction time, resource allocation path, etc. This is largely due to the fact that the model was developed taking into account real-time road network congestion (provided by the perception layer) and interdependencies between facilities (sewage pumping station power restoration should be prioritized) to select globally optimal routing and resource allocation schemes. This example demonstrates the model's ability to provide more scientific and effective decision support in complex real-life scenarios.

C. RESILIENCE ASSESSMENT FOR COMPLEX DISASTER SCENARIOS

Finally, a more complex composite disaster scenario (such as an earthquake accompanied by a secondary fire) was designed to test the model's performance under extreme stress and to evaluate its contribution to improving the resilience of urban infrastructure systems. In this scenario, multiple critical infrastructure nodes are damaged simultaneously, triggering widespread cascading failures.

At every time point after the disaster, the system function recovery rate using the dynamic adaptive scheduling model is significantly higher than that of the traditional solution. Especially in the third to fifth hours after the disaster, the gap in recovery rates stabilized at more than 10 percentage points. The fundamental reason for this phenomenon is that the two strategic decision-making bases are different. Static strategies may be useful in the initial stages of a disaster, but as the volume of fault information grows and system status changes drastically, their stated plans become obsolete. The result of this can be that a large investment is made in an irrepairable node or a secondary node, while the subsequent replacement node (which may be more critical) is ignored. When taking an example like this, a fixed planning situation may require that a main road into the city center be repaired, but due to an earthquake the road may be completely cut off by collapsed buildings and therefore cannot be opened in the near future.

On the other hand, the dynamic adaptive nature of the model has major advantages over a given time period. It is able to detect when major roads are completely congested and reassess network conditions in real time through a process of continuous sensing. The model integrates data

TABLE 2. Comparison of Historical Case Retrospective Analysis

Comparison Dimensions	Actual adopted solution	This model generation scheme	Performance improvements/differences
Delay from detecting water accumulation to issuing dispatch instructions	Approximately 25 minutes	Approximately 3 minutes (automatically triggered)	Delay reduced by 88%
Average time for the first rescue teams to reach the core flooded area	42 minutes	31 minutes	Time reduced by 26.2%
Resumption of traffic on major roads affected by flooding	3 hours and 15 minutes	2 hours and 48 minutes (estimated)	Recovery 13.8% ahead of schedule
Total mileage of resource scheduling path	158 kilometers	135 kilometers	Mileage decreased by 14.6%

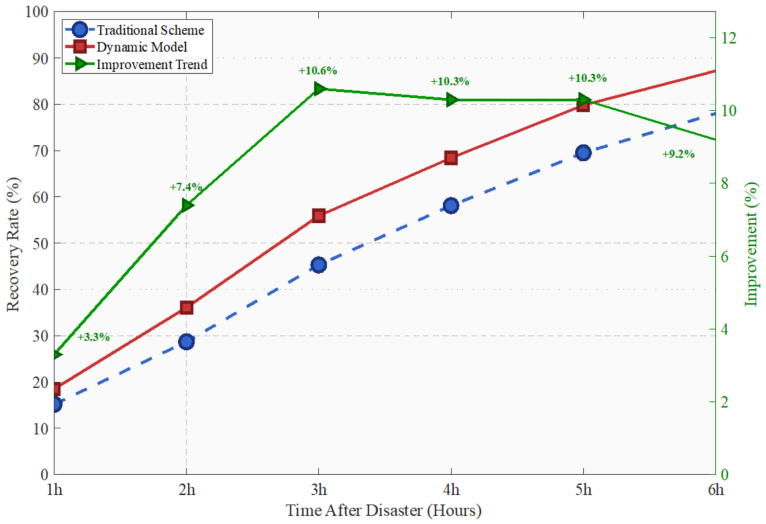

FIGURE 1. Comparison of the functional recovery process

from multiple sensors (such as vibration frequency analysis, satellite image change detection, and abnormal vehicle travel times) and uses a trained classifier to distinguish between temporary congestion (such as vehicle queues) and permanent structural collapses (such as road subsidence and bridge breakage). For example, when vibration sensors detect abnormal low-frequency signals and satellite images show surface deformation, the model determines it as a structural collapse and adjusts the repair priority accordingly. It can be found that there is also a secondary road that is not so seriously damaged in emergencies. Once repaired, it can be opened and become a new lifeline in key areas. The model will automatically and dynamically adjust the scheduling plan and reallocate resources to the repair tasks of the secondary road. Furthermore, the model is able to identify emerging critical centers in the development of a disaster. These dynamic changes in the importance of the network topology are implemented in the model through the risk simulation layer and immediately increase the repair priority of that substation. This is the dynamic optimization capability, which is the fundamental mechanism to greatly improve system flexibility.

V. CONCLUSION

The paper addresses critical infrastructure management challenges in smart cities, ranging from the backward dynamic risk perception of embedded sensor networks to the inability to evaluate cross-system impacts and the lack of efficiency in dispatching high-performance fiber-based emergency resources. It builds dynamic monitoring and emergency dispatch model on the basis of high precision spatiotemporal big data. The combination of multi-source heterogeneous data and creation of a digital twin view by fusing, simulation of risk cascading propagation through spatiotemporal graph convolutional networks and the forecast of a dispatch scheme through multi-objective adaptive optimization algorithm creates a shift of the paradigm between passive response to risk and active adaptation to proactively respond to it. Through experiments, it has been identified that the model is very good in identifying anomalies, predicting risks, as well as dispatch efficiency. Nevertheless, the model is very sensitive to the quality and completeness of data, practical implementation demands the aspect of cooperation between multiple departments and fiscal limitations. Future work will focus on lightweight deployment, uncertainty quantification, and federated learning architectures under cross-domain privacy protection to facilitate the integration of this model into real-world urban systems and distributed smart sensing networks.

AUTHOR CONTRIBUTIONS

Conceptualization – Yongxia Zhang, Xiaohua Huang, Rongnuan Wei, Mulan Wei, Hanshan Huang and Yanyang He; methodology – Yongxia Zhang, Xiaohua Huang, Mulan Wei, Hanshan Huang and Yanyang He; investigation – Yongxia Zhang, Xiaohua Huang, Rongnuan Wei, Mulan Wei, Hanshan Huang and Yanyang He; writing-original draft preparation – Yongxia Zhang, Xiaohua Huang, Rongnuan Wei, Mulan Wei, Hanshan Huang and Yanyang He. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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