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Predictive diagnosis of hidden risk for urban lifeline infrastructures driven by digital twin modeling of multisource observations: perspective

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Abstract: Hidden risks of service state of urban lifeline infrastructures under the complex environment or load are public safety information that must always be available. The point-measuring sensors commonly used now can only conduct observation of a certain parameter at a certain location, which restricts the ability to diagnosis hidden risks of infrastructures. With the digital twin (DT) model as the carrier and the structural effects as the essential element of series connections, low-cost point monitoring and new high-cost area detection (such as radar or images) data will expect to be efficiently integrated. This paper reviews the development and status of studies on structural monitoring, evaluation, and diagnosis. Three issues for addressing difficulties regarding the predictive diagnosis of structural hidden risks are summarized. Corresponding countermeasures and perspectives on the solution steps are given for the three bottleneck issues. After these processes are performed, theories and technologies system of integrated structural state-effect DT modeling and predictive diagnosis of hidden risks for the urban lifeline infrastructure can be constructed. Then, monitoring and detection data can be converted into structural diagnostic indicators, which will provide an effective implementation paradigm for the predictive diagnosis of hidden risks in lifeline infrastructures. The proposed perspectives can provide useful references for related research.

Keywords: urban lifeline infrastructures; digital twin; diagnosis of hidden risks; multi-source data fusion; structural health monitoring

1. Reviews of statuses

The urban lifeline (urban transportation, water, electricity, oil, gas, central heating network) is similar to a city's vascular network, and the urban lifeline infrastructures (including buildings, roads, bridges, tunnels, transmission towers, pipelines and other infrastructures in the networks of urban lifeline) are the main carrier of various physical and virtual objects in the city [1,2]. By the end of 2025, major developed countries in the world (including China) are expected to transition from an era of high-speed construction to an era of the coexistence of construction and maintenance for infrastructure. Because large urban lifeline infrastructure is often the main or only channel of the urban lifeline network it belongs to [3,4], its service state will influence the operational efficiency of the city [5,6]. Hence, when and which parts of it should be maintained are pieces of public safety information that must always be available [7,8].

The maintenance and management of large lifeline infrastructures worldwide have long relied on expert experience and regular inspection [9]. However, for a lifeline infrastructure with complex environments, loads, and structure types, regular manual or low-intelligence equipment (e.g., vehicle) inspections are time-consuming and labor-intensive and lack the ability to quickly provide feedback and synchronize information [10]. The monitoring data obtained from a structural health monitoring (SHM) system are not only a supplement to scientific research but can also provide the most realistic information about the action patterns of environments or loads and the structural effects under these environments or loads in real time [11]. The SHM system for the prototype of infrastructures could be an on-site laboratory, which could effectively help city administrators determine the real-time in-service behavior of existing lifeline infrastructures [12]. Nevertheless, the current technologies can only observe physical quantities online such as displacement, strain, acceleration, temperature, humidity, chloride ion concentration, and crack length and width. It cannot directly indicate the structural state changes and hidden risks (*i.e.*, the possible structural damage, local failure or overall failure of urban lifeline infrastructures in the future) behind the changes in physical quantities. Before their occurrence, these hidden risks will often be reflected via omens that abnormal changes in observed physical quantities. Preventing hidden risks before the omens appear of infrastructure is even more impossible. Hence, the theory, method, and technology on the diagnosis of hidden risk for lifeline infrastructures based on SHM need to be further developed and improved.

Since the introduction of SHM theory in fields from aerospace to civil engineering in the 1980s [13,14], this theory has often been applied to long-span bridges and other urban lifeline infrastructures. In the past decade, due to the rapid development of measurement, telecommunication, and computer technology, the theory and technology of online monitoring and degradation detection for structural service states based on intelligent processing and analysis of massive monitoring data have become increasingly mature [15–17]. The time needed to monitor the data of infrastructure from the front end (sensors) to the back end (monitoring center) and then to the terminal (maintenance and management engineers) has been significantly reduced. The real-time ability that long eluded SHM has received support due to updates and iterations in hardware technologies. It is now possible to model the service state of infrastructure and diagnose the hidden risks based on online monitoring data [18].

To date, most SHM systems use sensors to conduct monitoring of certain parameters (such as environmental temperature, wind speed or acceleration, strain, and displacement) at a certain point [19]. With the rapid development of modern radar/image observation and machine vision technologies [20–25], observation targets do not have to be fixed to a specific point but arbitrary area, and significant progress has been made in techniques for detecting fine-grained regional effects (including structural responses and apparent/internal faults) and evaluating structure states based on multi-source observation data [26–31]. For a SHM system only including the mode of point observation, if relevant practitioners lacking professional knowledge or long-term experience in structural engineering, a monitoring strategy must be used that has many sensors of various types to effectively capture the spatial distribution characteristics of various actions (*i.e.*, inputs of the structural system) and effects (*i.e.*, outputs of the structural system) of infrastructure [32]. Therefore, research on the optimal deployment of sensors is especially needed in the field of SHM [33], as it will address the barriers to the applicability of SHM. In recent years, with the rise of theories and technology related to big data, deep learning, and machine vision [34], processing and analysis abilities for various new types of area observation data based on synthetic aperture radar, images and other means have greatly improved [35–38]. Technologies such as image recognition for structural dynamic displacement and apparent faults, radar observation for structural spatial deformation, and ultrasonic testing for structural internal damage are widely used in information supplementation for short-term detection or long-term monitoring of large infrastructure [39–41]. Although the new method of area detection can observe the time-varying spatial effects of large infrastructure in a fine-grained manner, the cost of observation is significantly greater than those of traditional point monitoring methods, and the accuracy and stability of area detection are difficult to ensure in long-term operation and maintenance [42]. Recently, methods of monitoring—detection fusion for lifeline infrastructures have been gradually investigated by relevant scholars [43]. Nevertheless, these methods do not phase the equilibrium between the effectiveness and the cost of observation. Effectively integrating the results of traditional point monitoring and new area detection, and then quickly and accurately capturing the information of multiple fields' effects under complex environments and loads, as well as the knowledge of hidden risk for lifeline infrastructures are the keys to further improving intelligent operation and maintenance theory for future cities [44].

Besides multi-source data fusion, leveraging the extensive data generated by SHM systems for digital modeling represents another critical task for urban intelligent operation and maintenance. Digital twins (DTs) [45,46], as a new means of infrastructure informatization, digitization and intelligence that emerged after building information modeling (BIM) [47], emphasize the real-time nature of twin modeling more than BIM does and can better fuse multi-source and multimodal observation data. Unlike BIM and traditional numerical simulation (as shown in Figure 1), DT modeling and application entail constructing a virtual model that integrates data from physical infrastructure entities by digital methods, enabling simulation of the behavior and state of a physical entity in a real environment via a data integration model [48]. Through multiple information fusion, virtual reality interaction feedback, iterative optimization prediction and other means, DTs play the role of connecting the physical world and the information world and improve the level of maintenance and management of physical entities [49–51]. Therefore, for industrialized, fast-paced operation and maintenance scenarios with decreased manpower in the era of big data and 5G/6G, DTs have unique advantages in the fusion of multi-source monitoring/detection data, intelligent modeling via high-dimensional data, and other tasks [52].

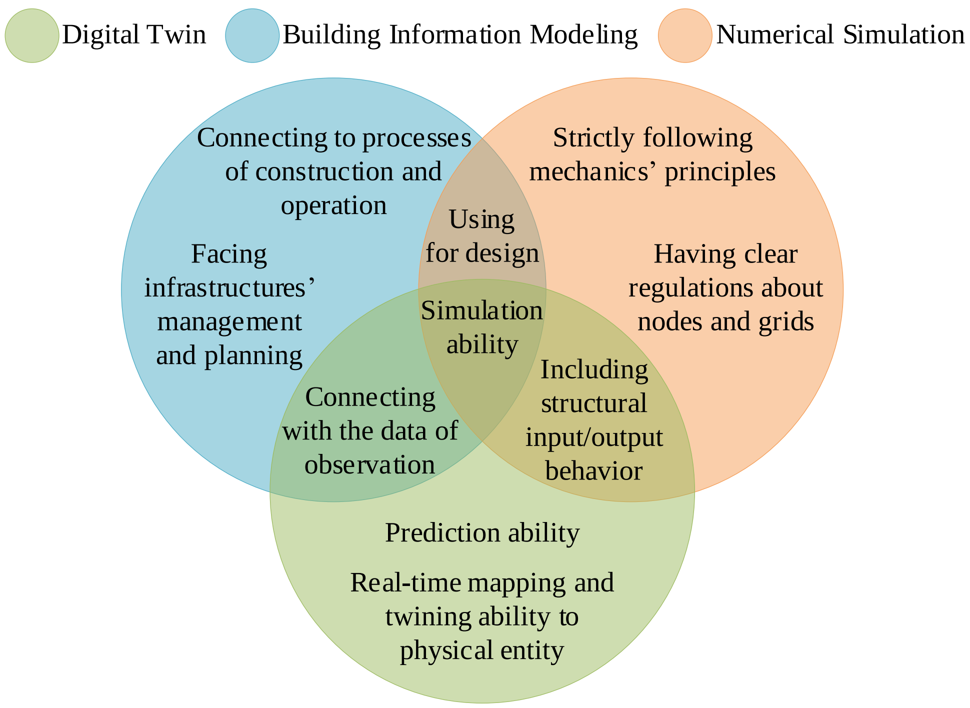

Figure 1. Advantages of three main types of theories for infrastructure informatization.

At present, research on DT-driven monitoring/detection, degradation prediction, health management, and risk diagnosis has been preliminarily conducted for spacecraft, machines, and infrastructure [53,54]. Some studies have achieved significant results [55–60]. The SHM system of a single large infrastructure will generate tens of gigabytes of data on average in a day, and the storage and processing scale for area detection data is larger [61,62]. Hence, it is necessary to establish an effective, economized and intelligent DT system to closely link the virtual model of data integration with the physical entities of infrastructures. This system will enable predictive diagnosis of hidden risks within infrastructure entities based on DT-driven deduction. In the DT system, extensive structured data provided by the SHM system is essential for constructing DT models for infrastructure monitoring. This trend stems from the urgent need for intelligent and economized operation and maintenance of large lifeline infrastructures, with the DT system serving as the carrier that integrates structural entities with the monitoring-detection-integrated data. The future goal is to predict hidden risks during the operation period of lifeline infrastructures. To achieve this goal, three main bottleneck issues must be solved, as described below section.

2. Countermeasures for issues

2.1. Seeking a balance between effectiveness and cost for the observation of large infrastructures under the constraints of limited sensing ability

The basic principle of structural monitoring and detection for large infrastructures is to observe structural actions and effects based on theories of mechanical, thermotic, acoustic, optic, electrical, or magnetic modalities [63], and subsequently evaluate the service states of structures based on the observation data. However, since the theory of structural monitoring and detection was proposed, point measurements using sensors as the main tool have dominated [64]. Although the results of sensor-based point monitoring have advantages in terms of accuracy, stability, and durability, a single sensor can only obtain a certain type of action or response for a very small part of the structure [65]. For large infrastructures, there are extremely high requirements for the type selection and location deployment of sensors [66]. With the development of tools such as machine vision, interferometric radar, and other new technologies for area detection, observations to the structural effects—including both area response and apparent/internal faults [67,68]—have truly expanded from independent points to distribution patterns, offering unprecedented advantages in capturing the spatial distribution features of effects. However, this has been accompanied by an exponential increase in observation costs [69]. Therefore, the issue can be addressed in three key steps. First, research should focus on developing methods and algorithms for feature parameter recognition in traditional point monitoring and new area detection, as well as on intelligent analysis techniques for the characteristics of multi-source big data. The second step involves investigating methods for balanced optimization and fusion-update algorithms for constrained point monitoring and area detection, grounded in real observational data and cost-efficiency considerations. Finally, a spatiotemporal distribution model should be constructed to represent complex multifield actions and their impacts on lifeline infrastructures, based on the principle of effectiveness—cost balance in observation. The model will enable the development of a functional mechanism for reverse optimization of observation strategies using real-time, multi-source big data. Completing these three steps allows for the efficient transformation of limited, sparse data into the spatiotemporal distribution characteristics of the entire structural field within allowable cost constraints, providing structured data support for DT modeling.

2.2. Dynamic modeling of time-varying states and structural effects for physical entities during the operation of lifeline infrastructures

Most real lifeline infrastructures during operation are a complex structural system with a high order of indeterminate degree, which follows the basic principles of mechanics [70]. The structural system of infrastructure can be in a good state of mechanical equilibrium in the early stage of service; as the service time of infrastructure increases, it will inevitably be eroded by the environment, loads, and even extreme disasters [71]. Additionally, the operating regimes of infrastructures can impact their structural effects; for instance, the load density and intensity on transportation facilities are significantly higher during peak periods compared to off-peak times. Prolonged exposure to high loads can lead to increased stress and strain within the structure, gradually accumulating damage over time [72]. Every process of external erosion may lead to a change in the mechanical equilibrium state of the structure [73], which is directly reflected in the structural effect of infrastructure under the in-service environment/load [74]. In theory, through digital modeling of the physical entities of lifeline infrastructures, the states of mechanical equilibrium of the structures can be simulated [75,76]. Finite element (FE) numerical simulation was an important and successful strategy in the early stages of digital modeling in the field of engineering [77]. However, FE theory, which is oriented toward design and analysis, does not emphasize the timeliness of modeling and updating. Although BIM theory has greater timeliness [78], it does not emphasize the functions of real-time mapping and twinning between physical entities and digital models. When facing the operation and maintenance scenarios of lifeline infrastructures, these two theories cannot indicate the current states and corresponding structural effects of infrastructure entities in a timely manner. Therefore, research should be conducted on economized modeling methods for the core mechanics of structures and components/members driven by multi-source point/area observation data. To enable the DT modeling of collapse and other situations that may not be encountered throughout the entire lifetime of the infrastructures, the constitutive relationships and other information about the entire process of failure obtained from experiments and calculations should be used. Constructing a dynamic DT model of time-varying states and structural effects provides precise real-time data to support the predictive diagnosis of latent risks. Then, the dynamic DT system will be able to make predictions regarding lifeline infrastructures.

2.3. Representation of multi-objective performance and predictive diagnosis of hidden risks for high-redundancy systems of lifeline infrastructures

To ensure the service life of lifeline infrastructures for more than a hundred years, infrastructures are usually designed and constructed as systems with high redundancy [79]. In the absence of extreme disasters, the influence of damage accumulation and performance degradation on structures generally does not reach a visible level [80]. However, along with each instance of damage and degradation, there is a slow change in the equilibrium state of the structural system, which may cause the entire/partial variation or redistribution of the structure/component’s effect under the same action (forces) [81]. Classical theories of structural design usually use parameters such as stiffness or flexibility matrices to represent structural performance [82]. However, for complex systems of infrastructure with high redundancy, it is very difficult to directly obtain the stiffness/flexibility matrix. Similarly, a single performance indicator is also often insufficient to comprehensively reflect the overall condition of lifeline infrastructures. For this scenario, establishing a fuzzy nonlinear relationship between structural state variation and structural effect (or its distribution) variation under the same magnitude of action based on observed big data is a feasible approach [83]. On this basis, because the DT system dynamically corresponds to the physical entities of lifeline infrastructures, it is possible to deduce and predict the safety, durability, availability and other multi-objective performance aspects of the structure and the effects of multi-objective performance in the virtual space [84]. Based on deduction and prediction results, it is also possible to infer whether there is a hidden risk in the current comprehensive service states of lifeline infrastructure physical entities [85]. This approach truly helps to overcome the bottleneck in existing technology systems, which struggle to perform predictive diagnosis before destruction, collapse, or another extreme event occurs [86–88]. Therefore, the multi-objective performance of structures should be represented in the digital twin environment driven by existing big data and online observation data. Subsequently, prediction and diagnosis techniques should be developed to enable the comprehensive and multi-objective analysis of service states and variations in their corresponding structural effects. This approach enables the effective diagnosis of latent structural risks before visible omens appear, thereby supporting preventive maintenance of lifeline infrastructures.

3. Discussions and perspectives

To meet the need for intelligent and economized operation and maintenance of in-service lifeline infrastructure in the new era, the key goals of ensuring safety, durability, and availability guarantee for lifeline infrastructures should be achieved according to the proposals for addressing the three main bottleneck issues in the above section. Mainly regarding the point monitoring–area detection fusion of observations and the use of DTs to diagnosis infrastructure deterioration of safety, durability, and availability, a series of possible innovations will be made (as shown in Figure 2):

First, theories should be developed for the intelligent processing of point monitoring data on structural actions and effects, as well as for optimizing measurement points.

Second, breakthrough technologies are needed for intelligently processing the area detection data on the distribution of structural effects and for updating the data through fusion.

Third, dynamic evolution systems of DTs for lifeline infrastructures are expected to be established via multi-source big data observation.

Fourth, predictive diagnostic approaches for identifying hidden risks of lifeline infrastructures based on the dynamic DT system must be proposed.

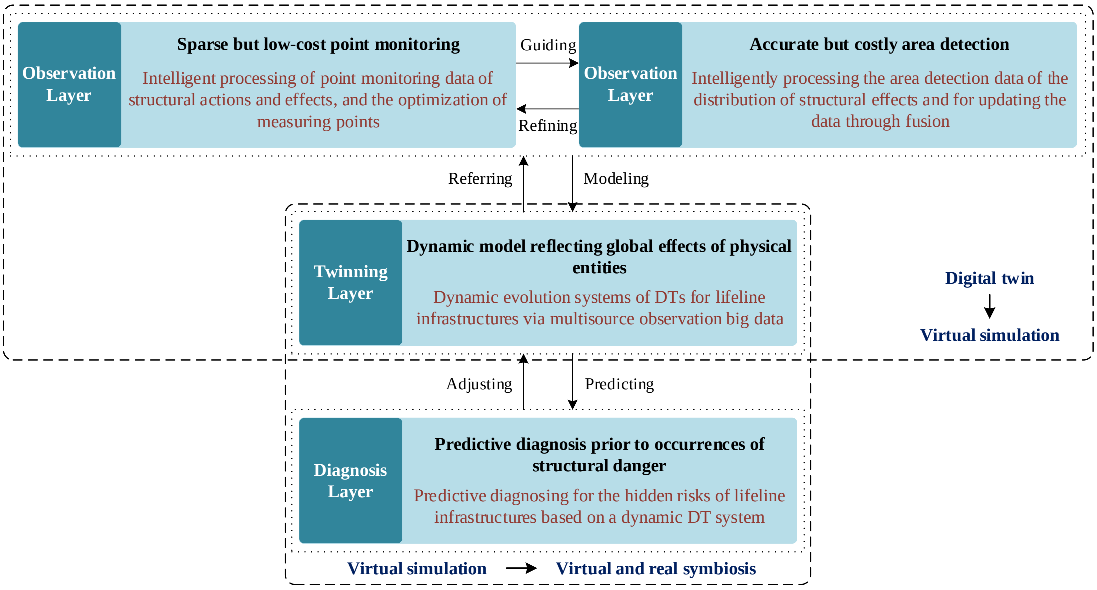

Figure 2. Four main innovative processes and their logical relationships.

In the observation layer, the sparse point monitoring results can guide area selection for area detection; conversely, accurate area detection results can refine the observation details outside the monitoring points. Then, based on the information from the observation layer, a dynamic model of the digital twin, which can reflect the overall effects of infrastructures online, can be truly established. Moreover, the concentration information (e.g., locations of maximum and minimum values) of structural effects (e.g., deformation, stress/strain) in the whole scope of the infrastructure can provide references for the adjustment of observation strategies. Finally, by using the DT system of lifeline infrastructures, the risks of events that have not yet occurred can be predicted, and the diagnosis layer will transmit relevant information to adjust the parameters of the DT system once the hidden risk has been addressed. A symbiosis between physical entities and the DT model is ultimately achieved.

After the above processes are performed, theories and technologies system of integrated structural state-effect DT modeling and predictive diagnosis of hidden risks for the urban lifeline infrastructure can be constructed; this system is driven by the fusion of point monitoring and area detection data. With structural effects as the essential elements of series connections, the entire process can be established and implemented: obtaining information and logical links from multi-source data fusion point monitoring and area detection, performing intelligent and economized DT modeling and multifield action effect deductions, and making predictive diagnoses regarding the structural comprehensive service state and the variations in its corresponding structural effects (as shown in Figure 3). Multi-source observation data can be intelligently transformed into a correlation index between structural comprehensive service states and structural effect variations. This index is required in real time by operation and maintenance managers of urban lifeline infrastructures to overcome the information barrier between the physical infrastructures entities and the DT system. It enables a complete process: DT → virtual simulation → virtual and real symbiosis, providing an effective implementation paradigm for the predictive diagnosis of the hidden risks of lifeline infrastructures. These achievements will provide scientific support for the intelligent operation and maintenance of urban lifeline infrastructures throughout their entire life cycle.

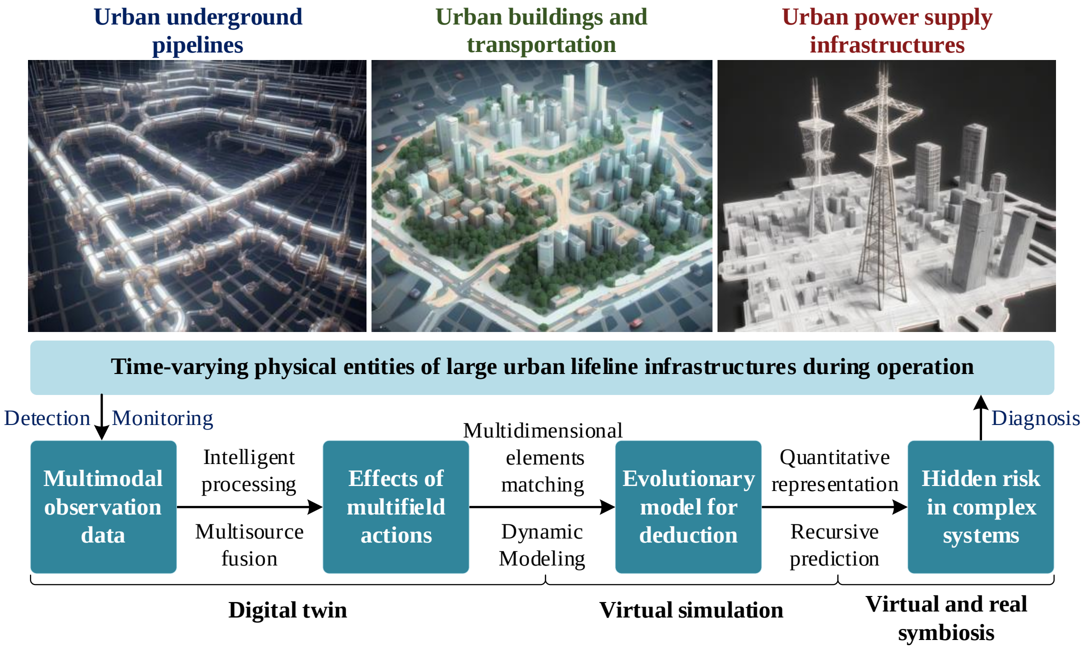

Figure 3. Core research points from DTs to virtual simulation to virtual-real symbiosis.

The core research points should include the following:

Observation method that balances effectiveness and cost and fuses monitoring and detection: This addresses the contradiction between the constraint of limited sensing points and global observation needs while ensuring effectiveness-cost balance. It also effectively integrates multi-source big data from traditional point monitoring and new area detection methods based on artificial intelligence, allowing for the capture of the characteristics of the spatiotemporal distribution of structural effects under complex multifield actions.

Twin modeling and deduction for structural effects under multifield actions: This solves the problem that traditional numerical simulation and updating methods have difficulty reflecting the real-time state of lifeline infrastructures. It establishes a dynamic DT system with multidimensional elements of time coordinate inputs and outputs to deduce structural effects under multifield actions for core mechanical systems related to the structure-component/member relationship.

Performance representation and hidden risk diagnosis for highly redundant systems: This overcomes the bottleneck that existing monitoring and evaluation technologies cannot detect potential problems before extreme events occur. DT-driven methods of safety/durability/availability performance representation and comprehensive service state prediction for urban lifeline infrastructures are proposed. This is followed by targeted prediction and diagnosis of the hidden risks in structures of highly redundant systems throughout their entire life cycles.

Of course, the above three points of core research are just the ideal prospects of the authors. To successfully complete them, a series of limitations need to be overcome: first, the life of sensors and systems is limited, replacement is hard to finish especially when the proposed strategies are applying on underground infrastructures such as pipelines; second, the scalability of relevant algorithms and models on different urban lifeline infrastructures needs to be ensured; third, data privacy and security need to be guaranteed. Similar limitations need to be resolved in the process of future technological applications.

4. Conclusions

Starting from the demand on the predictive diagnosis of hidden risk for urban lifeline infrastructures throughout their life cycles, this paper reviews the development and status of studies on structural monitoring, evaluation, and diagnosis. To address difficulties regarding the predictive diagnosis of structural hidden risks, three issues are summarized: the balance between the effectiveness and cost of large infrastructure observation, the dynamic modeling of time-varying physical systems of operational complex infrastructures, and the digital representation and predictive diagnosis of the multi-objective performance of structural states. Corresponding countermeasures and perspectives on the solution steps are given for these 3 bottleneck issues. A complete process from DTs to virtual simulation to virtual and real symbiosis for the full-field effects of lifeline infrastructures can be performed after these steps are completed. The complete process can help break the information barrier between infrastructure entities and DT systems. Then, monitoring and detection data can be converted into structural diagnostic indicators, which will offer an effective implementation paradigm for the predictive diagnosis of hidden risks in lifeline infrastructures and provide useful references for related research.

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Conflicts of interests

The authors declare there are no competing interests.

Authors' contribution

Conceptualization, Hanwei Zhao; methodology, Hanwei Zhao; resources, Youliang Ding and Tong Guo; data curation, Xiaonan Zhang and Jie Chen; writing—original draft preparation, Hanwei Zhao, Xiaonan Zhang, Jie Chen and Mingze Yuan; writing—review and editing, Youliang Ding, Tong Guo and Aiqun Li; supervision, Aiqun Li. All authors have read and agreed to the published version of the manuscript.

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