

# A bridge temperature field reconstruction method fused with sparse sensors data and structured grid-based deep learning approach

Miao Xu

*Department of Bridge Engineering, Tongji University; email: miao\_xu@tongji.edu.cn*

Limin Sun

*State Key Laboratory of Disaster Reduction in Civil Engineering; Department of Bridge Engineering, Tongji University; email: lmsun@tongji.edu.cn*

## ABSTRACT

The temperature is a critical environmental factor that impacts the safety and performance of bridge structures, to ensure the safe operation of bridges through Structural Health Monitoring, it is essential to investigate the temperature field of bridge structures. However, obtaining the full distribution of the bridge temperature field is challenging due to the complexity of the real bridge structures. The traditional temperature measurement methods are insufficient to accurately reflect the real temperature distribution of the bridge, in that limited number of temperature measurement points cannot capture the high non-uniformity of temperature field, and the finite element thermal analysis method is not promptly reflective of the temperature distribution of the bridge. To address this problem, a transient temperature field reconstruction method based on a structured grid-based deep learning approach is proposed in this article. The method integrates the data-driven sparse sensor global field reconstruction technology with the model-driven finite element thermal analysis methods to capture the spatiotemporal distribution pattern of the bridge temperature field. The proposed method is validated through a numerical example, and the impact of the quantity of the sensors and the snapshots on the reconstruction results is subsequently discussed. The results demonstrate that the proposed method can reliably reconstruct the transient temperature field of the bridge based on sparse temperature sensors accounting for the broken sensors existing. It can also obviously reduce the computation time compared to the traditional finite element method. This method promises a new solution to thermal analysis, which can help to monitor the key temperature metrics such as the average and gradient temperature and to lay a foundation for further thermal responses calculation of the bridge structures so that it can provide reliable support for bridge design and maintenance.

**KEYWORDS:** SHM; Bridge temperature field; Deep learning; Data reconstruction

## 1. INTRODUCTION

Bridge structures are subject to multiple temperature effects during service, such as daily and seasonal solar radiation, ambient temperature, etc., which exhibit a nonlinear and complex temperature distribution and effects. Relevant research and engineering experience have shown that in some cases, temperature effects can even control the structural design of bridges<sup>[1]</sup>, Moreover, it has been found that the dynamic response of structures is not only related to the characteristics of the structures themselves but also highly sensitive to environmental conditions such as humidity, wind, and temperature<sup>[2]</sup>. Therefore, exactly considering the temperature effects on bridges is necessary for long-term health monitoring of bridges.

The temperature field of a bridge is a function of both time and spatial coordinates, and is influenced by the bridge's environmental conditions. Factors such as radiation, convection, and

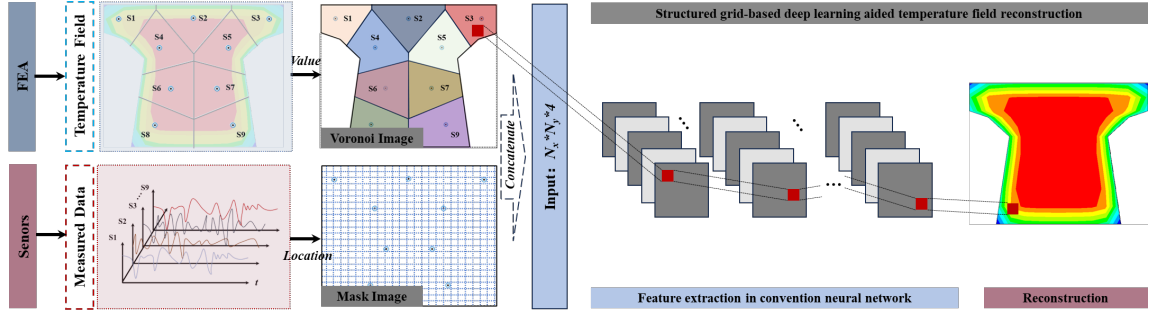
conduction can cause uneven distribution of instantaneous temperature on the surface and inside of the structure<sup>[3]</sup>.

The research methods for analyzing the temperature field of bridges mainly include field monitoring of actual bridges combined with numerical simulation analysis. In the early stages of temperature field calculation, researchers directly calculated the comprehensive temperature by using the air temperature and radiation, and applied it to the model as an equivalent environmental temperature<sup>[4-5]</sup>. Xia et al. directly applied solar radiation to the finite element model, which better reflects the actual temperature effects on the bridge tower structure. Based on this method, Xia et al. calculated the temperature effects of the cable tower and bridge deck of the Tsing Ma Bridge in Hong Kong, and the simulation results were validated by measured data<sup>[6]</sup>. Subsequently, the same calculation method has been widely applied to the analysis of concrete bridge towers<sup>[7]</sup>, and has been supported by measurement data in large projects such as the Hong Kong-Zhuhai-Macao Bridge<sup>[8]</sup> and the Sutong Yangtze River Highway Bridge<sup>[9]</sup>. It can also be further applied to the calculation of temperature effects such as cracking and displacement of concrete bridge towers in extreme climate conditions such as high-altitude and cold regions<sup>[10]</sup>.

Currently, there is a lack of research that combines finite element simulation and monitoring data to analyze the temperature field of bridges. It is therefore necessary to explore methods that utilize sparse monitoring data and finite element calculations to reconstruct the temperature field of bridges.

## 2. METHODOLOGY

Obtaining the temperature field of a bridge from monitoring data is essentially a global sparse reconstruction problem<sup>[11]</sup>, namely, the objective is to reconstruct a two-dimensional global temperature vector  $\mathbf{T} \in \mathbf{R}^{n_x \times n_y}$  from several sensor measurement data  $\mathbf{s} \in \mathbf{R}^{n_{sensor}}$  at locations  $\mathbf{x}_{s_i} \in \mathbf{R}^2$ . ( $n_x, n_y$  denote the number of grid points in the horizontal and vertical directions on a high-resolution field, and  $n$  represents the number of sensor measurements. And a part of sensors can be damaged in time.



**Figure 1.** Framework of structured grid-based deep learning approach for temperature field reconstruction

To achieve the goal of this study, we introduced Voronoi tessellation images into the input of the neural network to represent the influence of sensor data on its corresponding subregion<sup>[12]</sup> for the CNN, as shown below in Figure 1.

To use a CNN machine learning framework, the sensor data needs to be projected into an image file in an appropriate manner. Voronoi tessellation is a simple and spatially optimal projection of local sensor measurements onto the spatial domain. This tessellation approach optimally partitions a given space  $\mathbf{E}$  into several regions  $\mathbf{G} = \{\mathbf{g}_1, \mathbf{g}_2, \mathbf{g}_3, \dots, \mathbf{g}_n\}$  using boundaries determined by distances  $\mathbf{d}$  among  $n_{sensor}$ . Each points in  $\mathbf{g}_i$  are closer to the sensor points  $\mathbf{x}_{sensor_i}$  than to any other sensor points out of  $\mathbf{g}_i$ <sup>[13]</sup>. Therefore, input data consist

of two parts, the one is sensor measurements projected on Voronoi tessellation  $\mathbf{s}_V = \mathbf{s}_V(\mathbf{s}) \in \mathbf{R}^{n_x \times n_y}$ , shown in Figure 1 as Voronoi Image, and the other one is a mask image  $\mathbf{s}_m = \mathbf{s}_m(\{\mathbf{x}_{s_i}\}_{i=1}^{n_{sensor}}) \in \mathbf{R}^{n_x \times n_y}$ , which is used to store the location information of every sensors, defined as Eq.1:

$$\mathbf{s}_m = \mathbf{s}_m(\{\mathbf{x}_{s_i}\}_{i=1}^{n_{sensor}}) = \begin{cases} 1 & \text{if } \mathbf{x} = \mathbf{x}_{s_i} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

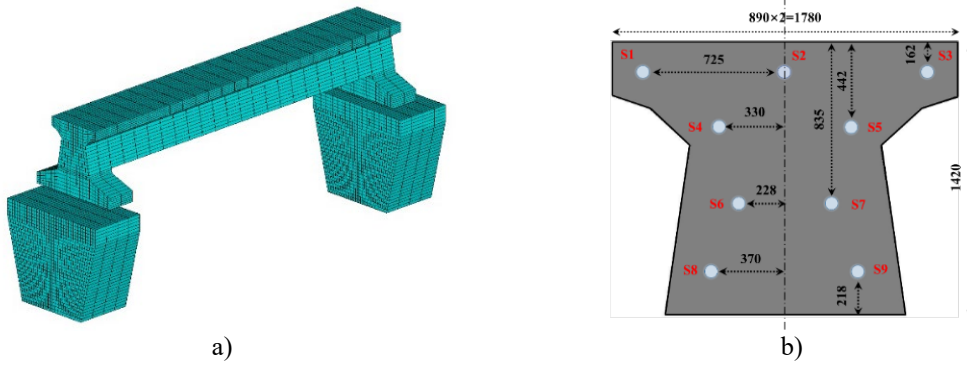
The spatial domains to be discretized by Voronoi tessellation and the high-resolution data are taken to be the same size. All grid points in each portion of the Voronoi image have its representative sensor value. As Voronoi tessellation provides a structured-grid representation of measurements from arbitrary placed sensors. The two input images above are provided to an 8-layer convolutional neural network, with the magnitude and position information of the sensors to reconstruct the temperature field of the bridge. The mean squared error (MSE) is selected as the evaluation metric for the neural network, defined as Eq.2:

$$MSE = \frac{\|T_{reconstruct} - T_{ref}\|_2}{\|T_{ref}\|_2} \quad (2)$$

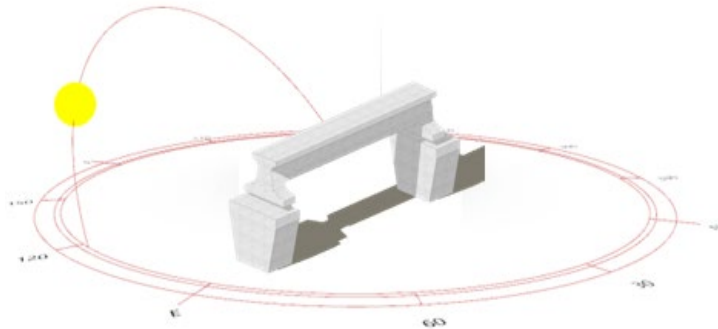
### 3. CASE STUDY OF A NUMERICAL SIMULATION

#### 3.1. Case introduction

To validate the effectiveness of this method for reconstructing the temperature field of bridges, a finite element numerical model based on a transient FE temperature field simulation was used for verification<sup>[14]</sup>. The maglev bridge FE model with three-dimensional thermal element SOLID 70 was established in ANSYS 2023 R1 software. The FE model has 19,152 elements and 21,892 nodes as shown in Figure 2. a), and 9 temperature sensors are arranged on the cross-section as shown in Figure 2. b).



**Figure 2.** Maglev bridge FE model and sensors location



**Figure 3.** Maglev bridge FE model and sensors location

The sun-earth relationship is simulated In Rhino software's Ladybug plugin. By combining the obtained sunlight information, the solar radiation values  $I$  are divided into three components: direct  $I_b$ , diffuse  $I_d$ , and reflected  $I_r$ , as shown in Eq.3.

$$I = I_b + I_d + I_r \quad (3)$$

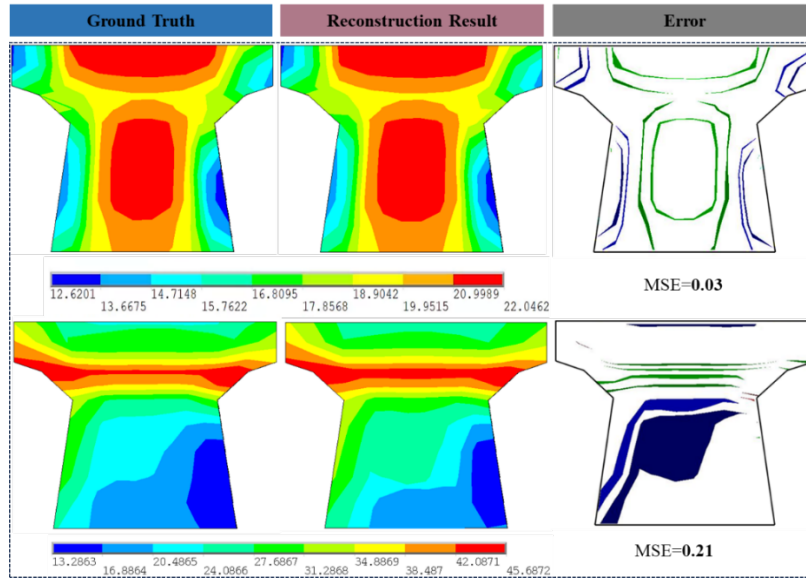
These components are then transformed into a comprehensive thermal boundary as shown in Eq.4:

$$-k \frac{dT}{dt} = (h_a + h_r) \left[ T - \left( T_a + \frac{\alpha I}{h_a + h_r} \right) \right] = (h_a + h_r) (T - T_e) \quad (4)$$

The temperature distribution was simulated for one year in ANSYS, with one time step per hour. A total of 4,800 snapshots of temperature distribution under different operating conditions were selected, including changes in environmental temperature under different weather conditions and differences in solar radiation caused by the passage of time. Then we used the deep learning method described earlier, using these snapshots as training and validation data, with a ratio of 7:3.

### 3.2. Results

Figure 4. shows the reconstructed result. The first operating condition is the temperature distribution at 21:00 at night, when there is no solar radiation on the bridge and only heat exchange with the outside world is occurring. Therefore, the bridge is in a state of heat dissipation, and the temperature distribution tends to be stable and uniform. In this case, the reconstruction effect is very good, and this method can accurately reconstruct the temperature distribution of the bridge at this time.



**Figure 4.** Display of the temperature field reconstruction results

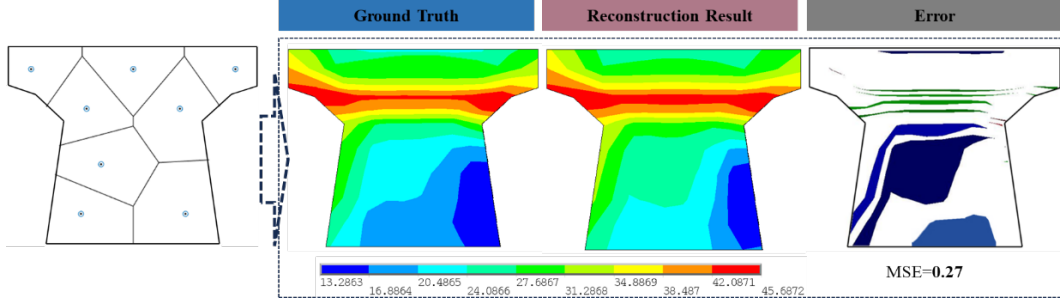
The second operating condition is at 11:00 in the daytime when the bridge is exposed to direct solar radiation. Therefore, the temperature distribution is significantly non-uniform. Although the reconstructed results using this method are still acceptable, the accuracy is much lower than that of the first operating condition with uniform temperature distribution.

### 3.3. Discussion

This section discusses the applicability of this method when a sensor is damaged and when

fewer snapshots can be gathered based on the above simulation cases.

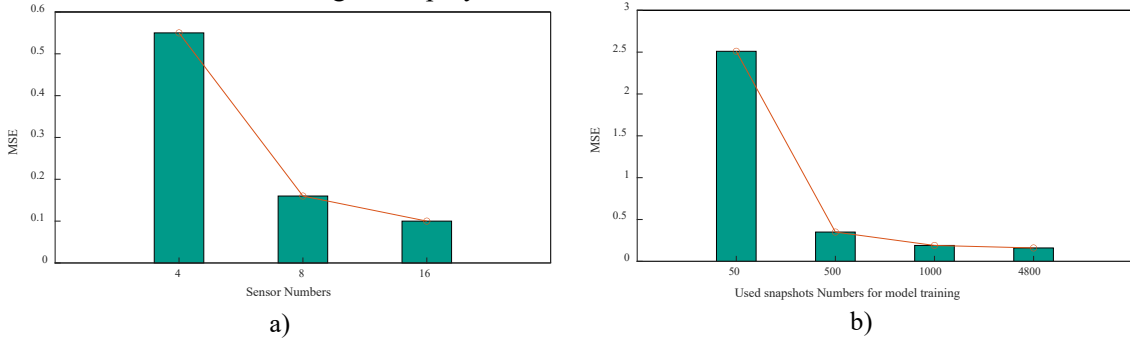
Firstly, suppose that S7 is out of service, and we only use the remaining 8 sensors for the reconstruction task, the Voronoi tessellation image of the cross-section would change accordingly. And we still used 4800 snapshots as the dataset to train and validate the model, and the results are shown in Figure 5.



**Figure 5.** Reconstruction result display with S7 out of service

It can be observed that when the data from S7 is missing, the reconstruction error increases significantly. Compared to the operating condition when all sensors work in proper situation, there are more obvious errors in the area where S7 is located. This is due to the lack of measurement data from S7 so it's hard for the model to learn relevant information. However, the reconstructed result is still acceptable when S7 is damaged overall.

Subsequently, the impact of the number of sensors on the reconstruction performance is discussed by comparing the reconstruction MSE using 4, 8, and 16 sensors with the same 4800 snapshots in Figure 6. a). It was found that the reconstruction accuracy improves as the number of sensors increases. The difference between using only 4 sensors and 8 sensors is particularly significant, indicating that the number of sensors is still limited to fully reflect the characteristics of the bridge temperature distribution. It should be noted that we did not discuss the different sensor deployment methods, but only correspondingly increased or decreased the number of sensors in the original deployment.



**Figure 6.** Reconstruction result comparison using different quantity of sensors

Finally, we briefly discussed the impact of using different numbers of snapshots on the results. It was found in Figure 6. b) that using 1000 or more snapshots can obtain better reconstruction results in this case, while using fewer snapshots leads to poorer results, in that the thermal behavior of bridges is complex and affected by various environmental factors. Fewer snapshots may miss some operating conditions, making it difficult to extract their features and leading to suboptimal reconstruction results.

#### 4. CONCLUSION

A structured grid-based deep learning method for reconstructing the temperature field of bridges is presented in this article. The method extracts temperature distribution features from finite element analysis to train neural network models, and uses temperature sensor data to

reconstruct the temperature field. The feasibility of the method and its applicability when sensors fail were verified through numerical model case, which shows a fine result in temperature field reconstruction in certain conditions.

However, this article is only an attempt to combine monitoring data with finite element thermal analysis to construct a temperature field model of bridges. Moreover, the deep learning method itself is relatively dependent on the completeness of the dataset. Therefore, the next step is to further validate and improve its applicability by combining it with actual monitoring data.

## ACKNOWLEDGEMENTS

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