Journal of Civil Structural Health Monitoring (2021) 11:149–173
https://doi.org/10.1007/s13349-020-00444-x

ORIGINAL PAPER

Structural health monitoring research under varying temperature condition: a review

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Received: 14 June 2020 / Revised: 11 September 2020 / Accepted: 9 October 2020 / Published online: 31 October 2020

Abstract

Suffering from solar radiation, day–night replacement and seasonal changes, the structure will produce notable temperature behaviour, which has a vital effect on the long-term process of the health monitoring. Previous studies show that there is a significant correlation between the measuring responses and temperature from health monitoring systems. To analyse the structural state more accurately, much literature employed health monitoring methods considering temperature effects. This paper reviews technical research concerning health monitoring of civil structures under varying temperature. Firstly, the correlation researches of structural measuring responses (dynamic and static responses) and temperature are reviewed, which includes the researches of the influence mechanism and the data statistics, and the studies of the influence of non-uniform temperature on responses are also reviewed. In addition, different types of separation and forecast methods of the temperature-induced part of the structural responses data are summarized, followed by a brief summary of benefits and drawbacks of these methods. Lastly, the recently proposed process frameworks of damage assessment considering temperature effects are also introduced.

Keywords Structural health monitoring · Temperature effect · Damage detection

1 Introduction

During the long-term service life, affected by comprehensive factors, large infrastructures (e.g., bridges and buildings, etc.) suffer from damage accumulation and resistance deterioration, or even collapse in some severe cases. Structural health monitoring (SHM) technology is a significant approach to ensure the safety and reliability of the structures, which uses the continuous and real-time monitoring data to identify structural damage and track structural integrity [1, 2]. In the past few decades, SHM was one of the focus areas of civil engineering, and a large number of methods were proposed based on the vibration responses (e.g., acceleration, frequency, mode, etc.) and the static responses (e.g., static displacement, stress, strain, etc.) [3–6].

Ultimately, SHM technology is an inverse process of structural design and verification reflecting the variations of structural material parameters and geometrical characteristics with the change of structural responses. But many field monitoring data indicate that structural responses are not only related to the characteristics of the structure, but also highly susceptible to the environmental conditions, such as humidity, wind, and most importantly, temperature [7]. Taking bridge as an example, Farror et al. [8, 9] performed several modal tests on the Alamosa Canyon Bridge in New Mexico, USA, and found that temperature has an imperative influence on the natural frequencies, and that the changes in the first three natural frequencies over 24-h are about 5.0%,

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this level is higher than the variability caused by vehicle weight in the tests. Duan et al. [10] applied the correlation analysis to quantify the correlation between strain and temperature, based on the measurement data from a tied arch bridge, whose results revealed that temperature changes effect on strain of the bridge are significant. Ding et al. [11] studied the expansion joint displacements under normal environmental conditions for the Runyang Suspension Bridge based on long-term continuous data, which showed that the variations of displacement are highly correlated with the variation in temperature compared with the wind speed. As a consequence, either the vibration or static responses, the effect of temperature is one factor that cannot be ignored. To obtain more accurate structural damage alarm and condition evaluation results, considering the environmental factors reasonably during the analysis has received more and more attention. In recent years, many related work about the influence of environmental temperature on the monitoring process has been studied, and various methods to deal with this influence have been proposed.

In this study, the advances in SHM methods considering temperature effect are reviewed. Firstly, the related mechanism researches on the effects of temperature on structural monitoring responses are introduced, including the studies of structural vibration modal parameters and static response. In addition to the mechanism researches, the statistics and related verification work of the relationship between temperature and structural responses data in the field monitoring system are summarized. Generally, as well as ambient temperature, the changes of the structural responses are the result of the comprehensive effects, such as traffic load, structural damage, etc. The influence of ambient temperature will interfere with the estimate of the effects of other factors. To make a more accurate assessment, it is necessary to forecast and separate the temperature-induced parts of the overall responses, for the purpose of this, many methods have been used, such as regression analysis (RA), support vector machine (SVM), artificial neural network (ANN), principal component analysis (PCA), etc. According to whether temperature data is used in the process, these methods are divided into two parts to be introduced in the passage, i.e., input and output methods and output-only methods. The final goal of forecasting and separating temperature-induced responses (TIR) is to effectively identify damage and assess safety of a structure under the effects of the environmental factor, based on dynamic or static data, many process frameworks that integrate multiple methods have been developed recently, which greatly improve the effectiveness and robustness of structural monitoring under environmental changes. In this paper, the research of these damage assessment frameworks is also sorted out.

The rest of the paper is organised as follows. Section 2 presents the influence mechanism researches of temperature, and summarizes the correlation statistics of temperature and structural responses (modal parameters and static responses) based on the SHM system data, which are divided into two subsections to introduce according to different response types. In addition, the researches of effect of non-uniform temperature are also reviewed in Sect. 2. Section 3 introduces the forecast and separation methods of the temperature-induced part of the structural responses. Section 4 reviews the process frameworks of the damage detection and structure identification methods considering temperature effects, to correspond to the previous Sect. 2, this section is also divided into two subsections: vibration-based methods and static-based methods.

2 Correlation between temperature and structural monitoring responses

2.1 Correlation between temperature and modal parameters

Vibration-based analysis is one of the widely studied SHM methods for overall structures. In essence, structural damage is considered as a reduction of structural feature parameters, such as mass, stiffness, etc., which is intuitively reflected as changes in structural modal parameters (e.g., natural frequencies, mode shapes, etc.), therefore, Damage assessment of the structure can be performed with the variation of modal parameters. However, matters are seldom as simple as this, numbers of field monitoring data and theoretical analysis show that the structural modal parameters are not only related to the structural feature, but also susceptible to environmental factors, especially temperature changes [12].

In recent years, some researchers have dedicated to studying the mechanism of the effect of temperature change on natural frequency. Using theoretical analysis and experimental verification, Xia et al. [12] alleged that the main factor affecting the structural natural frequency with temperature is the change of elastic modulus, but the process ignored the influence of temperature-induced internal forces. Li and Zhang et al. [13] discussed the temperature effect factors on the natural frequency, including variations of elastic modulus, deformations, structural internal force and boundary conditions induced by temperature, and the effects of both uniform and non-uniform temperature distributions case was investigated.

To illustrate the mechanism, a partially restrained beam with a longitudinal spring at the right end is considered, which is subjected to a uniform temperature change δT (assuming that is positive), as shown in Fig. 1, according to the Euler beam theory, the free vibration equation of the structure can be expressed as follow,

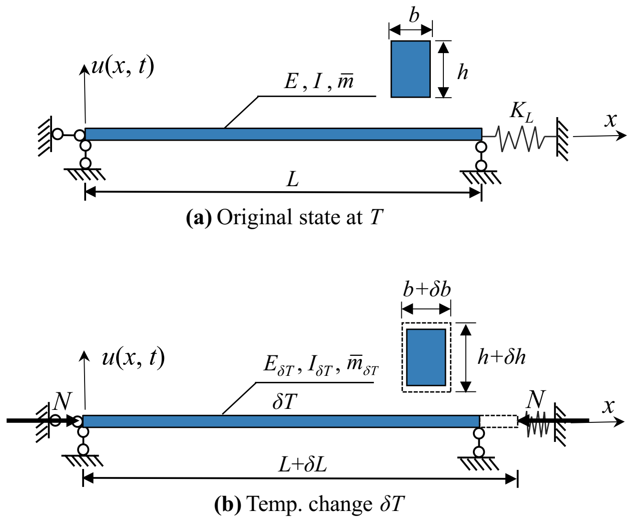


Fig. 1 Example of a partially restrained beam model subject to uniform temperature change

$$EI\frac{\partial u^4(x,t)}{\partial x^4} + N\frac{\partial u^2(x,t)}{\partial x^2} + \overline{m}\frac{\partial u^2(x,t)}{\partial t^2} = 0, \tag{1}$$

deriving Eq. (1) gives the natural frequency f_n of the nth order as [14],

$$f_n = \frac{(n\pi)^2}{2\pi L^2}\sqrt{\frac{EI}{\overline{m}}\left(1 + \frac{NL^2}{n^2\pi^2 EI}\right)}, \quad n = 1, 2, \ldots, \infty, \tag{2}$$

where $u(x, t)$ is the vibrational displacement of the beam at the horizontal x at time t; L is the length, I is the moment of inertia; $\overline{m}$ is the linear density, E is the elastic modulus, and N is the structural reaction force caused by the temperature deformation being restrained.

It can be seen from Eq. (2) that the influence of temperature changes on modal parameters mainly comes from several aspects [13]:

- First, the temperature change will cause the material properties (elastic modulus) to change. When the temperature changes, the elastic modulus of the material changes, which can be expressed as:

$$E_{\delta T} = E \cdot \left[1 + \frac{\delta E}{E}\right] = E \cdot \left[1 + \theta_E \cdot \delta T\right]. \tag{3}$$

  Although the elastic modulus change with temperature is considered to be the main factor of the variability of natural frequencies, there are not consensus of its quantification. According to the Refs. [12, 15–19], the elastic modulus changes linearly with temperature at the natural environment (−20 to 60 °C). For concrete, steel and aluminium, the linear temperature coefficient θ_E is $-\,3.0 \times 10^{-3}$/°C, -3.6×10^{-4}/°C, and -5.6×10^{-4}/°C, respectively, but in Ref. [20–27] the variation of the elastic modulus with temperature is described as the nonlinear relationship, as shown in Fig. 2.
- Second, because of the thermal expansion and contraction effect, the temperature change will cause the structure deformation, one obtains,

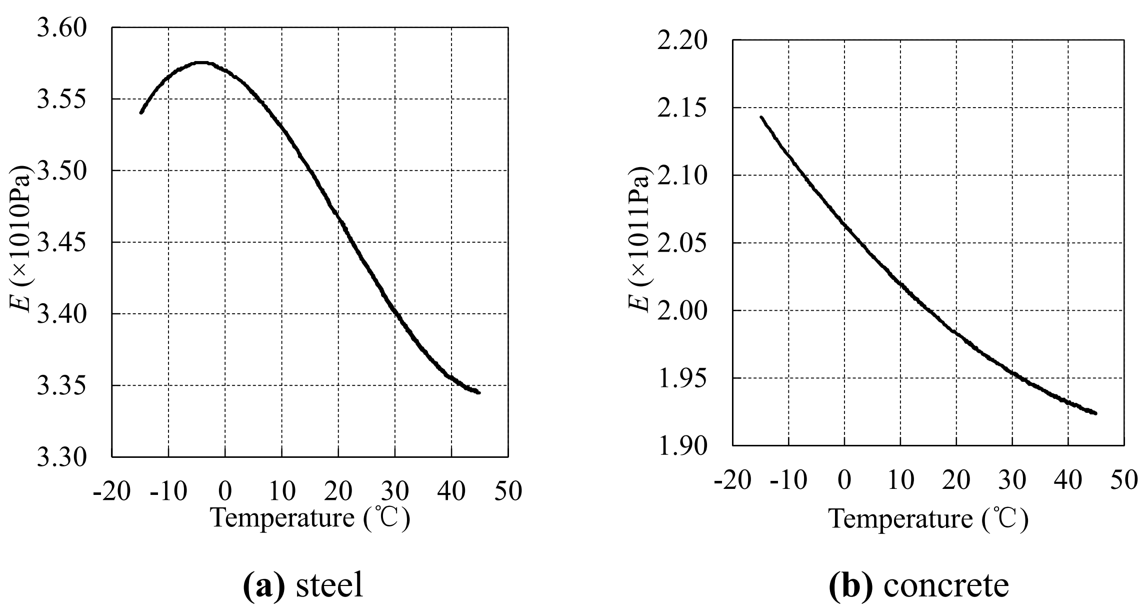


Fig. 2 Young modulus of the two materials versus temperature

$$\frac{\delta L}{L} = \alpha \cdot \delta T\ ;\ \frac{\delta I}{I} = 4\alpha \cdot \delta T\ ;\ \frac{\delta \overline{m}}{\overline{m}} = -\alpha \cdot \delta T \tag{4}$$

where α is the thermal coefficient of linear expansion of the material, for concrete, steel and aluminium, the value is 1.0×10^{-5}/°C, 1.1×10^{-5}/°C, 2.30×10^{-5}/°C, respectively [12–15].

- Third, due to the existence of boundary conditions, the temperature deformation of the structure is constrained to the structural reaction force N, which affects the natural vibration characteristics of the structure, as Eq. (2). But this influencing factor is more difficult to quantify, since the temperature internal force is directly related to the boundary condition. If the constraints (e.g., structural support stiffness) change is caused by temperature, it will indirectly affect the structural dynamic characteristics, such as changes of restraints in the end bearings caused by colder weather [28–30].

With the advancement of vibration testing technology and data storage method, more extensive correlation studies of temperature and modal parameters of structures have been conducted based on long-term data collected from SHM systems, and most of these researches are aimed at natural frequency. This is probably due to a number of reasons. On one hand, compared with other modal parameters, natural frequency is easily measured by a small number of sensors directly, which results in its broad range of applications in SHM and facilitates its long-term change trend research [3, 31]. On the other hand, the effect of temperature on the mode shape and damping ratio is more complicated than the natural frequency, in addition, due to the complexity of modal testing progress, statistical results of the correlations between mode shape, etc. and temperature are more susceptible to other uncertainties. For example, Ni et al.'s [32] modal analysis of the Ting Kau bridge shows that the mode shapes at different locations fluctuate differently over time and have no obvious correlation with temperature. The modal experiment of Balmes et al. [33] also shows that the temperature change has little effect on the mode shape. After analysing the vibration data of the Dowling Hall Footbridge for a period of time, Mosera and Moaveni [34] found that the identified damping ratios are significant scatter and have not obvious pattern of variation. Li and Zhang et al. [13] studied the relationships between modal parameters and temperature, and indicated that the correlation between Modal Assurance Criterion (constructed by modal shapes) and temperature is less than 0.2, and the damping ratios of different order have different correlations with temperature.

In comparison, more literatures published in recent years are focus on the correlation between natural frequencies and temperature, and because of its importance to public safety, bridge is the main research object. The SHM system of Ting Kau Bridge is one of the success applications (Fig. 3). Based on the vibration data collected from the system, Zhou et al. [35] found that the natural frequencies have a negative correlation with temperature, but the measured data are more discrete and the nonlinear characteristics are obvious, as shown in Fig. 4.

Researches of the temperature effect on natural frequencies of other building structures have also been reported. For example, to ensure the safety of Guangzhou New TV Tower during the construction stage and the long-term service stage, a sophisticated SHM system which contains several accelerometers has been established by the consortium of the Hong Kong Polytechnic University and the Sun Yat-Sen University [36, 37], Xia et al. [12] studied the variations in the modal properties based on the acceleration data from 9:00 of 15-January-2009 to 11:00 of 16-January-2009, lasting 26 h. The variations in the first four frequencies and temperature at different hours are shown in Fig. 5. As can be seen, the natural frequencies of the structure generally decrease when the temperature goes up, though variations in the frequencies are very small. The results of modal analysis of National Aquatics Center by Li et al. [13] indicated that the frequencies variation with the temperature for both February-2008 and May-2008 are illustrated in Fig. 6. It is clear that the second and third frequencies go up with the increase in temperature, and the first frequency shows a slight decrease with increase of temperature. To study the effects of changes in temperature on the natural frequencies of slender masonry buildings, a monitoring system is applied in an Italian monumental bell tower by Ubertini et al. [38]. The analysis of monitoring data of more than 9months

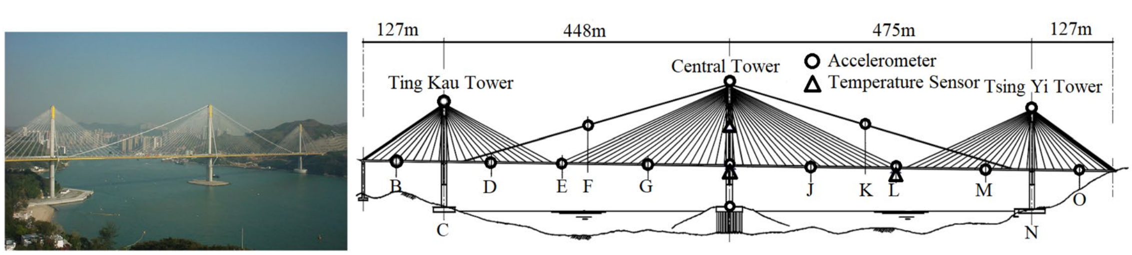


Fig. 3 Ting Kau Bridge and the layouts of temperature sensors and accelerometers on it [35]

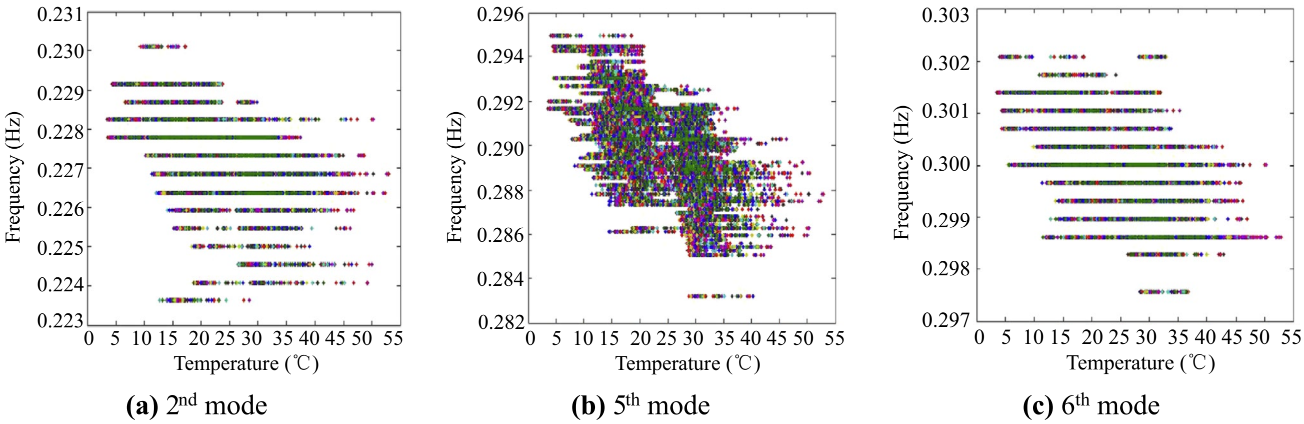


Fig. 4 Measured natural frequencies versus average temperatures of Ting Kau Bridge [35]

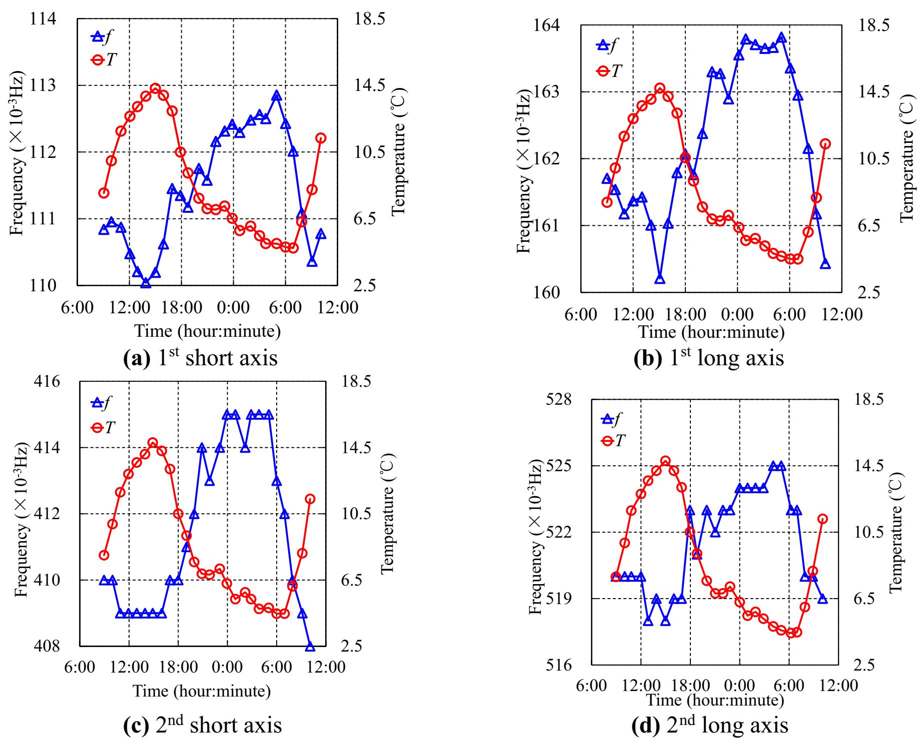


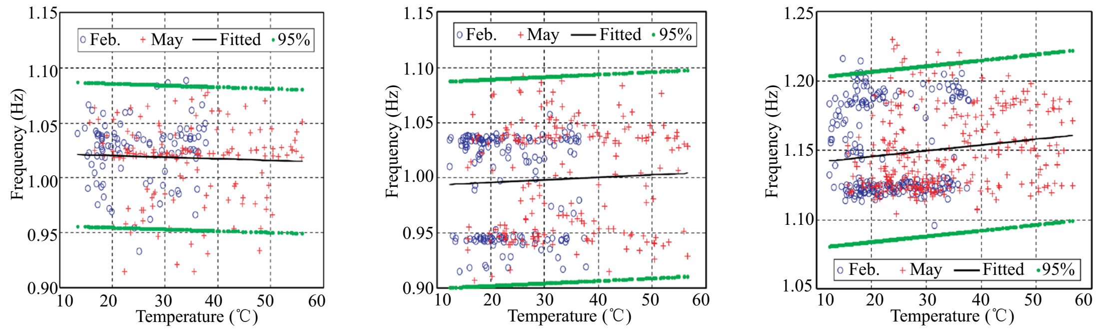
Fig. 5 Variations in frequencies versus temperature of the Guangzhou New TV Tower [12]

shown that dry bulb temperature variations can produce significant changes in natural frequencies, up to 16 MHz/°C.

In addition, as the limitation of space, other researches about the correlation between temperature and natural frequency are summarised in Table 1, published from 2001 to 2019. Most of these studies are devoted to bridge, and others include high-rise buildings and large-spatial steel structures, historic buildings, etc.

2.2 Correlation between temperature and static responses

Although the vibration-based monitoring methods can effectively inspect and evaluate the overall state of a structure, the complicated analysis and high-frequency sample of the vibration data limit its use in some SHM systems. In comparison, the static responses are more widely used in long-term health monitoring, due to its reduced requirements of data collection and analysis, these static data types include



(a) 1st mode (East-West) **(b)** 2nd mode (South-North) **(c)** 3rd mode (Vertical)

Fig. 6 Natural frequencies versus temperatures of China National Aquatics Centre [13]

strain or stress, displacement, deflection, rotation angle, etc. Under normal service conditions, affected by the time-varying environment, temperature-induced parts are one of the main components of these static, and sometimes even exceeding the responses caused by traffic or other load.

To fully explain the mechanism of TIR, several researches have been conducted combined with field monitoring data [47–50]. To illustrate the concept of TIR simply, still take a partially restrained beam as an example [47], as shown in Fig. 7, which is subjected to a uniform temperature increase (δT). Attention to the structural deformation at the right spring support, the total deformation (Δ_{tot}) is a combination of the thermal deformation (Δ_{th}) and the restrained deformation (Δ_{r}) and can be expressed as,

$$\Delta_{\text{tot}} = \Delta_{\text{th}} + \Delta_{\text{r}} = \alpha \cdot \delta T \cdot L + \frac{\sigma}{E} \cdot L. \tag{5}$$

The mechanical strain (ε_{M}) is defined as the restrained part of the strain, resulting from restrained deformation (Δ_{r}) that produces mechanical stress σ, and total deformation (Δ_{tot}) is defined as the measured movement of the structural bearing or joint that does not produce mechanical strain, which can be calculated as shown in Eqs. (6) and (7), respectively,

$$\varepsilon_{\text{M}} = \frac{-K_L \alpha L}{\text{EA}\left(1 + \frac{K_L L}{\text{EA}}\right)} \cdot \delta T \tag{6}$$

$$\Delta_{\text{tot}} = \frac{\alpha L}{1 + \frac{K_L L}{\text{EA}}} \cdot \delta T. \tag{7}$$

It can be seen from Eqs. (6) and (7) that the mechanical strain and the total displacement are directly related to structural stiffness (EA) and boundary stiffness (K_L). In this way, the mechanical strain and the total displacement can be used to analyse the health condition of the structure or the support [47–51].

In addition, since TIR (e.g., $\varepsilon_{\text{M}}, \ \Delta_{\text{tot}}$) is directly related to temperature changes δT, the static response usually shows a periodic law similar to temperature changes. In general, temperature changes could be divided into seasonal and daily ones from timeline, which is expressed as [52],

$$\delta T = \delta T_{\text{ssl}} + \delta T_{\text{dly}} = \left(T_{\text{ref}} - T_0\right) + \left(T - T_{\text{ref}}\right) \tag{8}$$

where δT_{ssl} and δT_{dly} are the seasonal and daily temperature component, usually have a period of 24 h and 365 days respectively, T_{ref} is a reference temperature, and T_0 is the initial one at structural closure instant. Temperature changes occur rather gradually, thus, when using static responses to assess the condition of the structure, it is reasonable to use hourly averages of temperature to discuss temperature changes and their corresponding effects [53]. Figure 8a is a hourly temperature data time-histories from an actual monitoring structure of more than 1 year, two obviously different scale periods (annually and daily) of temperature change can be observed intuitively, which may cause the static responses also varies annually and daily. Figure 8b is the frequency spectrograms corresponding to the data in Fig. 8a, it can be clearly seen that two significant frequency peaks appear around $0.0001 \times 1/3600$ Hz (corresponding to a period of 365 days) and $0.0417 \times 1/3600$ Hz (corresponding to a period of 24 h), which further confirms that the periodicity of the seasonal and daily of the temperature change and its corresponding TIR. Recently, the difference between the static responses of the structure under the two temperature change cycles has also been attended and studied, readers who are interested in more information should refer to the references [54].

As the durability and reliability of the SHM system improves, a large amount of data has been accumulated, based on the simultaneous acquisition data, more statistics

Table 1 Correlation studies of temperature and natural frequency based on the dada from SHM system

Proposed by	Test time	Structure	Materials	Remark
Peeters et al. [28, 39]	1 year	Z24-Bridge (Switzerland)	RC	The relation between temperature and frequency can roughly be described by two lines, with the knee situated around 0◦C
Fu et al. [29]	1 year	A 2-span slightly skewed continuous bridge	Steel & RC	The first three frequencies increase as the temperature decreases below approximately 60˚F and that there is little change for temperatures above this level
Ni et al. [32, 40], Zhou et al. [35]	1 year	Ting Kau bridge (Hong Kong, China)	—	When the temperature varies from 3 °C to 53 °C, the 1st and 8th natural frequencies of the bridge change by 6.7% and 1.7% respectively
Desjardines et al. [41]	6 months	Confederation bridge (Canada)	RC	A clear trend of reduction in the modal frequencies with increase in the average temperature of the concrete of the bridge
Liu et al. [42]	5 years	A curved posttensioned bridge	RC	In 1st–3rd mode, the natural frequencies decrease as the temperature rises, the regression show that the first three frequencies decrease by 0.5%, 0.7% and 0.3% respectively when the temperature increases by 1 °C
Nayeri et al. [43]	1 day	A full-scale 17-story building	Steel	There is a strong correlation between the modal frequency variations and the temperature variations
Li et al. [44]	16 days	Yonghe bridge (Tianjin, China)	RC	The normal environmental changes accounts for variation in modal frequencies with relative difference from 1.47 to 3.16%
Yuen et al. [45]	1 year	A 22-storey building	RC	There is high correlation between the modal frequencies and the ambient temperature, for the three concerned modes, the natural frequencies increase as the temperature rises
Faravelli et al. [46], Xia et al. [12]	1 day	New TV Tower (Guangzhou, China)	Steel	The frequencies generally decrease when temperature goes up and increase when temperature goes down
Li and Zhang et al. [13]	—	National Aquatics Centre of China (Beijing, China)	Steel	The 1st frequency decreases with an increase of temperature, whereas the 2nd and the 3rd frequencies go up as temperature increases. The variations in frequencies are about 1% at a temperature range of 40 °C
Xia et al. [12]	1 day	Ting Kau Bridge (Hong Kong, China)	—	The frequencies generally decrease when temperature goes up and increase when temperature goes down, the changes of natural frequencies are mainly caused by the change of modulus of material at different temperature
Moaveni et al. [15]	17 weeks	Dowling Hall Footbridge (Medford, USA)	Steel and RC	Natural frequencies show significant variability during the monitoring period, and ambient temperature is the most influential factor of the changes. The natural frequencies increase as the temperatures decrease, and this increase is much more significant when temperatures go below the freezing point

Table 1 (continued)

Proposed by	Test time	Structure	Materials	Remark
Ubertini et al. [38]	9 months	San Pietro bell tower (Italy)	Masonry	Temperature variations can produce significant changes in natural frequencies, up to 16 MHz/°C
Regni et al. [16]	5 months	A 10-story frame building	RC	Temperature variations and wind intensity have a clear effect on the three natural frequencies and the corresponding damping ratios
Kita et al. [17]	1 year	Consoli Palace (Italy)	Masonry	An almost perfectly linear temperature correlation is observed for natural frequencies of most modes, whereas frequency-temperature correlations of some modes are better represented by quadratic regression lines, highlighting more complicated temperature-driven mechanisms

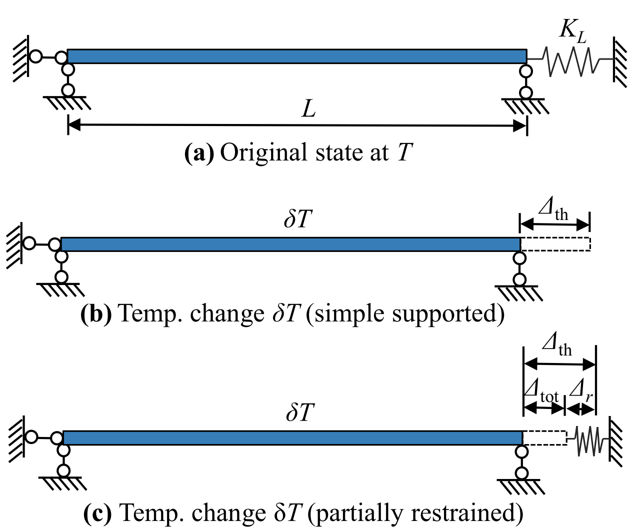
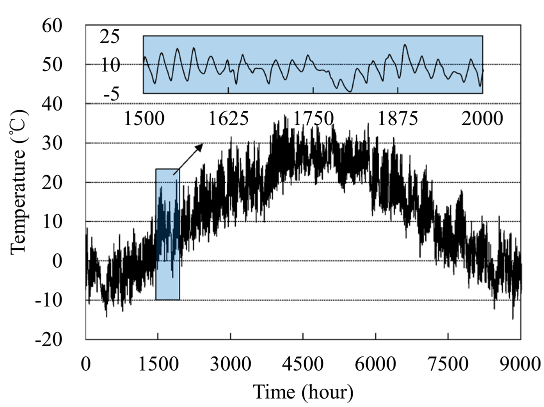


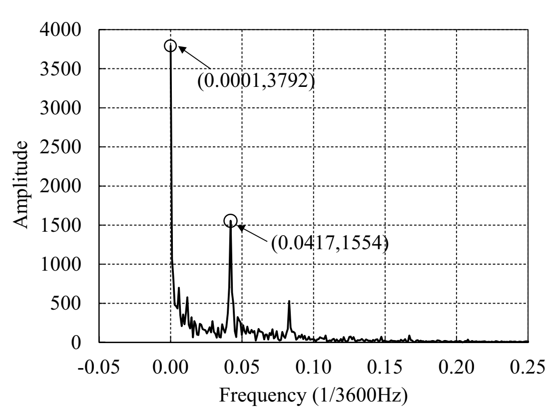
Fig. 7 Schematic diagram of the mechanical strain and unrestrained displacement of a partially restrained beam model subject to uniform temperature change

between the static responses and temperature have been performed, and clearer correlation have been verified. For example, based on the long-term measurement data from the SHM system of the Runyang suspension bridge, Ding et al. [11] studied the effect of temperature on the expansion joint displacements, result reveal that measured displacements are observed to increase with an increase in temperature, as shown in Fig. 9. Using existing structural health monitoring systems on a large-span suspension bridge, Xia et al. [55, 56] plotted the time histories curves of typical longitudinal strain and temperature responses measured on a cross section of the main girder (Fig. 10). It can been seen that the shape of the time course curve of the two is basically the same.

Large-span spatial steel structures are also temperature-sensitive structural forms, significant thermal deformations are often observed on these structures. A large number of long-term monitoring work of the large-span spatial structures has been carried out by author's team, which is used for temperature related research. For example, Fig. 11a shows



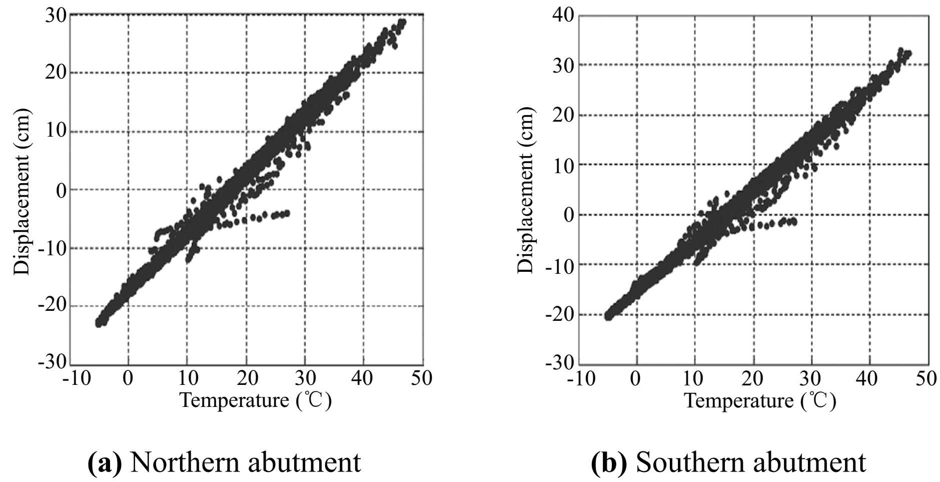
(a) Temperature data in time domain for 2 years



(b) Temperature data in frequency domain

Fig. 8 Temperature data in the time and frequency domains

Fig. 9 Correlation between expansion joint displacements and temperature of Runyang suspension bridge [11]



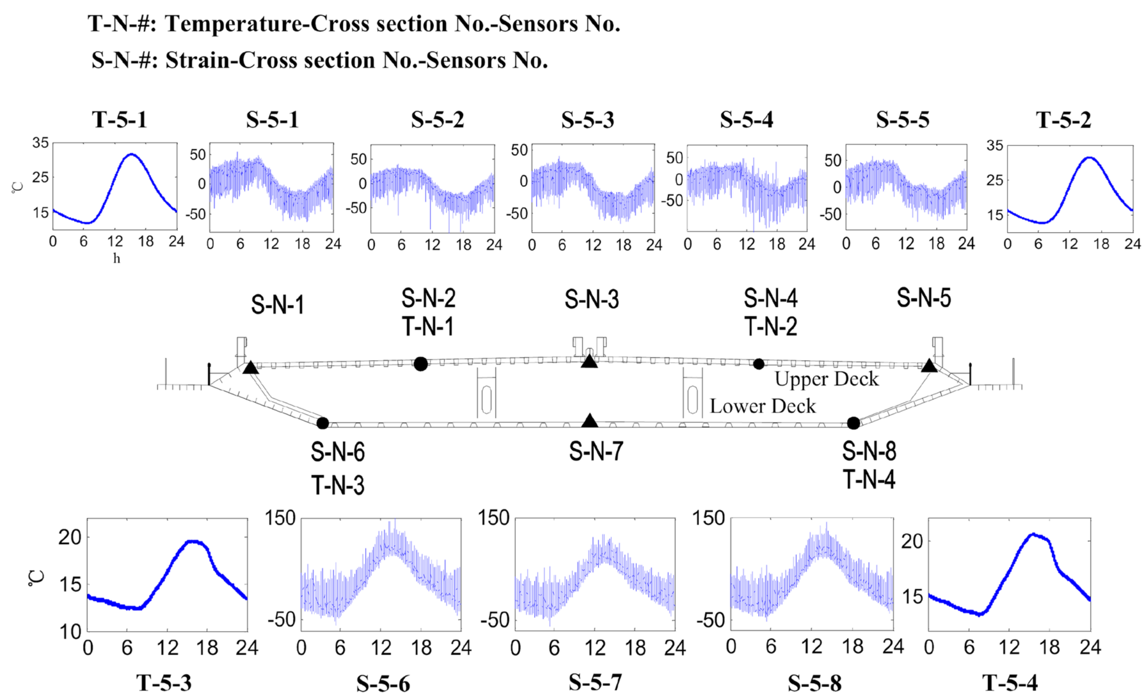


Fig. 10 Typical daily strain and temperature time histories on the mid-span of a suspension bridge [55]

the main components of a hangar roof structure at Beijing Daxing International Airport (BDIA), which consists of an upper grid and lower trusses. Sensors for stress and temperature monitoring have been placed on the structure to ensure the safety of the key components during service. The time-histories of the temperature and stress in a certain period are shown in Fig. 12, and their sensors positions are shown in Fig. 11b–c upper and lower represent the upper surface and lower surface of the member, respectively. As can be seen from Fig. 12, the temperature and stress are positively correlated at some measuring points (Fig. 12a), while at some other points, the correlation are negative (Fig. 12b).

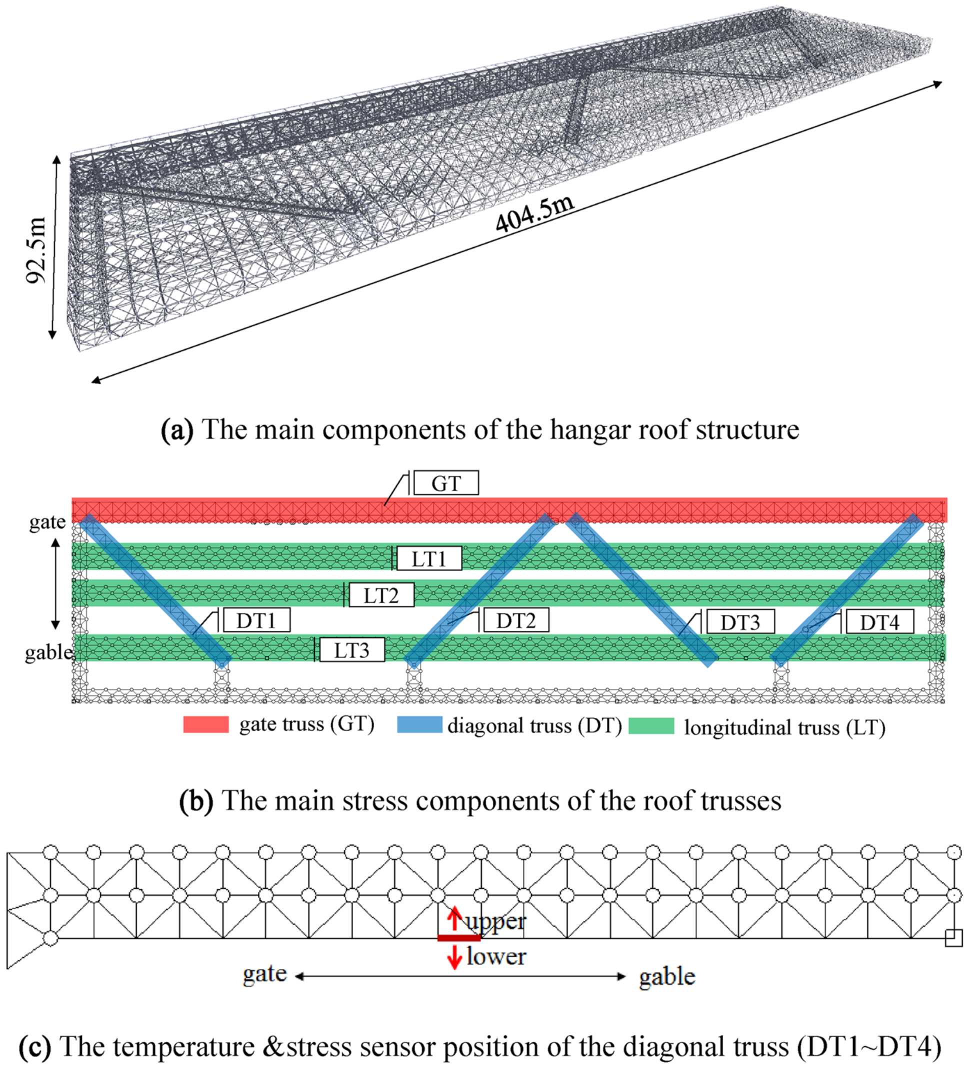
In addition to the above, other researches about the correlation between temperature and (quasi) static response are summarised in Table 2.

As can be seen from Table 2, most of the (quasi) static response-temperature correlation statistics from the SHM system are focused on the mechanical strain (corresponds to stress) of the component and the unrestrained displacement at the structural bearing or joint.

2.3 Non-uniform temperature effects

Compared with seasonal and daily fluctuations of air temperatures, solar radiation is a relatively more complex

Fig. 11 The schematic diagrams of the hangar roof structure at BDIA and its sensor layout



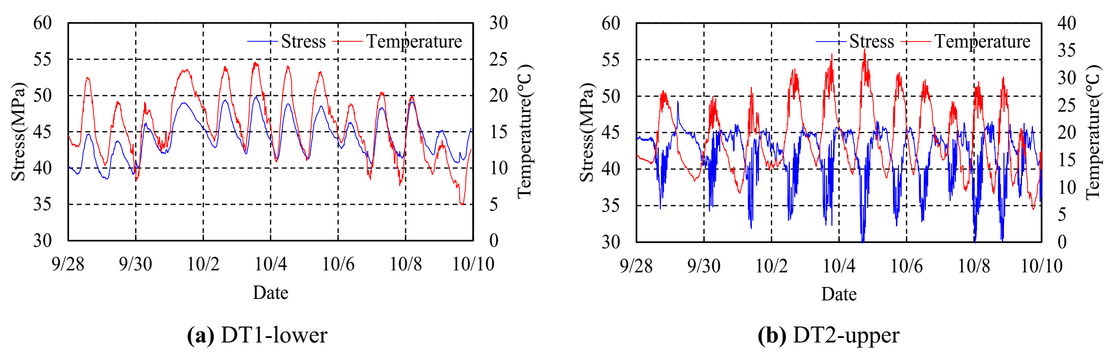


Fig. 12 The time-histories of temperature and stress of the hangar roof structure

environmental factor. Effected by solar radiation, the temperature distribution on a large structure is usually non-uniform, which leads to the correlations between temperature and structural responses of different components or different positions is not uniform. These non-uniform temperature effects can be roughly divided into two categories. One of them is the vertical temperature gradient (VTG) which is caused by the large cross-sectional size of the structures. Xia et al. [63] studied the effect of non-uniform temperature gradient on the natural frequencies of a simply supported RC

Table 2 Correlating research of temperature and (quasi) static responses based on the dada from SHM system

Proposed by	Data length	Structure	Materials	Monitoring parameter	Remark
Ni et al. [58]	1 year	Ting Kau bridge (Hong Kong, China)	—	Displacement	The temperature fluctuation mainly accounts for the movement of the expansion joint
Liang et al. [59]	1 month	Dafosi Yangtse River bridge (Chongqing, China)	RC	Strain	Strain and temperature data have a highly linear positive correlation
Li et al. [60]	7 day	Yonghe bridge (Tianjin, China)	RC	Strain	The maximum distribution of slowly changing strain are caused by temperature and dead loads
Duan et al. [10]	1 day	A tied arch bridge	RC	Strain	The temperature effect on responses of the structure may not be negligible and may mask the response caused by the live loads or structural damage
Ding et al. [11]	148 days	Runyang suspension bridge (Zhenjiang, China)	RC	Displacement	An overall increase in displacement is observed with an increase in the temperature of the bridge, there is a linear correlation between 10-min mean displacement and temperature
Luo et al. [57]	1 year	National Stadium of China (Beijing, China)	Steel	Stress	The stress variation was notable under uniform temperature field action, and the member stress is linear to its temperature
Xia et al. [55, 56]	1 year	A long-span suspension bridge	RC	Strain	The strain curves exhibit a similar trend to the temperature curves, and the peaks of the temperature and strain time histories have an approximately 1-h delay in a day
Lyu et al. [51]	1 year	Historic timber building (Lhasa, China)	Timber	Strain	The measurements on the column over 1 day and 1 year show clearly that structural strain responses closely follow the temperature cycle implying that temperature variations play a key role in determining deformations of these components
Hu et al. [61]		Guangzhou Canton Tower (Guangzhou, China)	Steel	Displacement	Temperature has a linear effect on the structural responses, the relation between the tower top displacement and structural temperature can be represented by a linear regression equation
Kita et al. [17]	1 year	Consoli Palace (Italy)	Masonry	crack amplitudes	The amplitudes of two major cracks show a marked linear decreasing trend with increasing ambient temperature
Lee et al. [62]	11 months	Gwangan bridge (Busan, Korea)	RC	Tilting angle	The tilting angle of the first pylon has a strong correlation with temperature

slab, the result shows that there is a good linear correlation between the natural frequencies measured and the structural temperature distribution other than the air temperature. Liu et al. [64] studied the characteristics of temperature gradients in steel–concrete composite girder of a long-span cable-stayed bridge by analysing the large amount of data in the long-term temperature field test, two profiles for positive vertical temperature gradient and one profile for negative vertical temperature gradient are proposed. Reilly and Glisic [65] proposed two classes of methods to identify time periods of minimal thermal gradient on a structure, which is based on the range of raw temperatures and the distribution of the local thermal gradients.

Another kind of non-uniform temperature effect is caused by the spatial shape of structures, due to the complexity of the large structures, the components at different positions have different temperature values. The long-span cable-stayed bridge is one of the typical structures affected by this non-uniform temperature, which has attracted more attention in recent years. Xia et al. [66] studied the temperature distribution and related responses of the Tsing Ma Bridge through a combination of numerical analysis and field monitoring, it was found that the thermal response of different bridge components (deck, cable, tower, etc.) is obviously different. Zhou and Sun [54] simplified the structural temperature field of the cable-stayed bridge as three parts: girder, tower and stay cable, then the different modes of temperature–response correlation of the girder length and mid-span deflection have been proposed. Jang and Smyth [67] used the full-scale finite element to simulate the long-span cable-stayed bridge, and generated spatially varying temperature over the bridge model randomly, the effect of the spatial temperature distribution on the natural frequencies has been studied. The large-span spatial structure is also a typical structure affected by the spatial temperature distribution, based on the long-term measurement of stress and temperature of National Stadium of China, Luo et al. [57] found that stress variation caused by non-uniform temperature field is larger than that caused by uniform temperature field action at some parts such as the top chords.

In short, both of the VTG and the temperature difference between different components are relatively complex structural thermal problems, and may require comprehensive measurement setups and reasonable numerical model to capture these effects adequately. To clarify the effect of non-uniform temperature on the structural responses, further researches on this issue are needed in the future.

3 Methods of forecasting and separating of the temperature-induced responses

According to Sect. 2, either for vibration responses or static responses of the structures, temperature is an important factor of fluctuations in their daily data. The purpose of SHM is to detect damage and warn anomaly timely by analysing these data. Therefore, it is necessary to forecast and separate the environmental factors, especially temperature-induced responses, so that the structural safety condition can evaluate more effectively. In recent years, many different solutions have been proposed, which can be roughly divided into two categories from whether temperature data are required:

- Input and output methods: Using the data of temperature (input) and structural responses (output) simultaneously to separate and forecast the temperature-inducing part of the responses.
- Output-only methods: The data of temperature are not required, rather environmental effects are treated as embedded variables. The structural responses are only needed when separating and forecasting the temperature-inducing part of the responses.

3.1 Input and output methods

3.1.1 RA

RA takes the structural response as a function of temperature, and estimates the value of the dependent variable, which is considered to be the temperature-induced part of the response. Linear regression (LR) model is one of the simplest and most widely used RA method, the progress of LR is shown in Fig. 13. It assumes that temperature and structural response are strongly linearly related, hence the temperature data from a single point can be used as the input to estimate the structural response, whose explicit expression can be expressed as,

$$\hat{Y} = \hat{a} \cdot T + \hat{b} \tag{9}$$

where the estimated values $\hat{a}$ and $\hat{b}$ of the parameters in Eq. (9) can be determined by the available data from the SHM system, then the temperature-induced response $\hat{Y} \in \mathbb{R}^{1\times n}$, namely the estimate of measured response $Y \in \mathbb{R}^{1\times n}$, can be obtained the further by the temperature

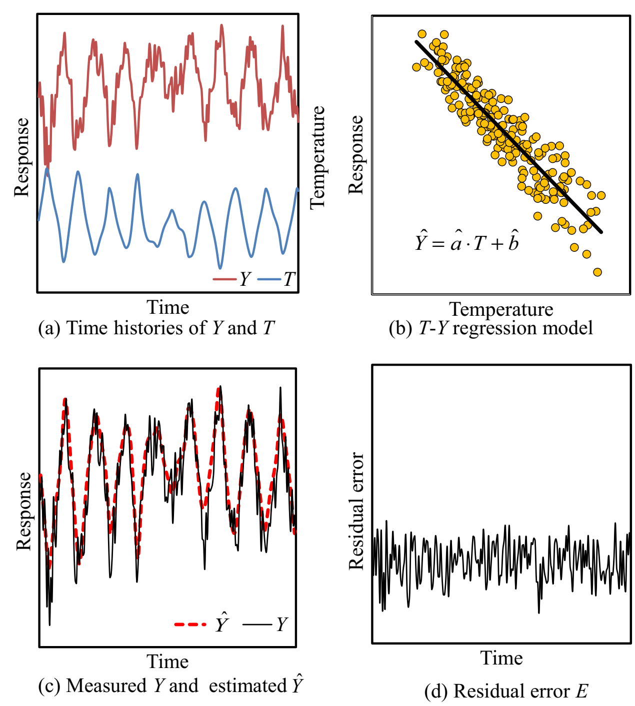


Fig. 13 A schematic presentation of LR model for separate the temperature-induced responses

data $T \in \mathbb{R}^{1\times n}$. Moreover, the residual error E is derived as follows:

$$E = Y - \hat{Y} \tag{10}$$

which includes the information of the structural response with the effect of temperature factor removed, such as predicting error, noise and other load effects, etc. Duan et al. [10] and Liang et al. [59] used the LR model to analyse the correlation between the strain and temperature monitoring data of the bridge, and then used the residual of strain after removing the temperature trend to alert damage or overload. Based on the long-term data of expansion joints displacement and temperature of Runyang Suspension Bridge, the LR model have been established by Ding et al. [11], which was used to normalize all of the measured displacements to a fixed reference temperature before the correlation analysis of traffic-displacement and wind-displacement. To adjust the temperature-induced changes in natural frequencies that are used for damage detection, Kim et al. [31] performed a set of empirical frequency correction formulae which are derived from the relationship between temperature and frequency ratio by LR model.

As the temperature load of a structure is a kind of field load, for large structures, the temperature load is not the same for all parts due to the non-uniform temperature distribution. Therefore, it is more reasonable to use the temperature data of multiple measuring points to the model. A multiple linear regression (MLR) model with the temperature data of multiple measuring points as input is expressed as:

$$\hat{\boldsymbol{Y}} = \begin{bmatrix} \hat{Y}_1 \\ \hat{Y}_2 \\ \vdots \\ \hat{Y}_q \end{bmatrix} = \begin{bmatrix} \hat{\beta}_0 & \hat{\beta}_1^1 & \hat{\beta}_1^2 & \cdots & \hat{\beta}_1^p \\ \hat{\beta}_0 & \hat{\beta}_2^1 & \hat{\beta}_2^2 & \cdots & \hat{\beta}_2^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \hat{\beta}_0 & \hat{\beta}_q^1 & \hat{\beta}_q^2 & \cdots & \hat{\beta}_q^p \end{bmatrix} \begin{bmatrix} 1 \\ T_1 \\ T_2 \\ \vdots \\ T_p \end{bmatrix} = \hat{\boldsymbol{\beta}}\boldsymbol{T} \tag{11}$$

$$\left(\hat{\boldsymbol{Y}} \in \mathbb{R}^{q\times n},\ \ \hat{\boldsymbol{\beta}} \in \mathbb{R}^{q\times(p+1)} \text{ and } \boldsymbol{T} \in \mathbb{R}^{(p+1)\times n}\right)$$

where $\hat{Y}_i \in \mathbb{R}^{1\times n}$ $(i \in 1, 2, \dots, q)$ is the the temperature-induced response at location i, i.e. the estimated value of the ith monitoring response $Y_i \in \mathbb{R}^{1\times n}$ $(i = 1, 2, \dots, q)$, $T_j \in \mathbb{R}^{1\times n}$ $(j = 1, 2, \dots q)$ is the temperature data of the jth temperature measurement point, $\hat{\beta}_i^j$ is the estimated value of β_i^j, that is thermal effects of jth temperature measurement point on the ith response. Sohn et al. [68] established a MLR model of temperature and natural frequencies, and applied the trained model to new monitoring data to check whether the newly detected natural frequencies matched the specified confidence level. This level of confidence was used to determine whether the natural frequency changes were caused by temperature changes or stiffness degradation. Xia et al. [63] employed the MLR to establish the relationship between the temperature data at different measurement points of the cross section and the first natural frequency, which discovered that the natural frequency has a better linear relation with the temperature values at different points of the cross section than with the surface temperatures only. Hu et al. [61] proposed a regularized MLR method to establish the quantitative relation between the displacement and temperature data at different facades and sections of the Canton Tower in different seasons, then the temperature-induced and wind-induced displacement of the structure have been separated. For the cable-stayed bridge, considering the temperature difference between the cable, girder and tower; and the temperature gradient of the girder and tower, Xu et al. [53] proposed a method combining finite element model and MLR to separate the thermal effects.

To obtain good fitting results, in addition to the linear regression method, some quadratic and multiple polynomial regression (MPR) models have also been used to analyse the correlation between temperature and structural responses, more details about these methods can be found in Refs. [15, 34].

3.1.2 SVM

SVM is a paramount statistical learning algorithm to study data relations, which can not only solve pattern recognition problems such as classification, but also can be used for regression analysis of data. SVM technique is applied to formulate the dependence of the input and output of the system and accurately determine the nonlinear relationship between them, so sometimes it referred to as support vector regression (SVR). The basic principle of SVM can be briefly expressed as follows: first, map the original dataset to a higher-dimensional feature space, and then use the optimization method to find the hyper plane that best separates the dataset in this transform feature space. Using the temperature data $\boldsymbol{T} = [T_1, T_2, \dots, T_j, \dots, T_p]^{\mathrm{T}}$ of the p temperature points in the health monitoring system as input, the process of predicting the structural response using SVM is shown in Fig. 14 [40], the decision function used for the estimation can be expressed as:

$$\hat{Y} = f(\boldsymbol{T}) = \sum_{i=1}^{n} v_i \cdot K\left(\boldsymbol{T}_i, \boldsymbol{T}\right) + b \tag{12}$$

where $K\left(\boldsymbol{T}_i, \boldsymbol{T}\right) = \left\langle \Phi\left(\boldsymbol{T}_i\right), \Phi(\boldsymbol{T})\right\rangle$ is a kernel function, $\Phi(*)$ is represented as a mapping function, $\langle *, * \rangle$ is an inner product, $\boldsymbol{T}_{\mathrm{i}}$ is the support vector, v_i is the weight factor to each kernel function, and b is an offset; the temperature data $\boldsymbol{T}$ and the structural response data Y which are used to train the model can be selected from SHM system, and the SVM model is established by calculating the v_i and b by a suitable

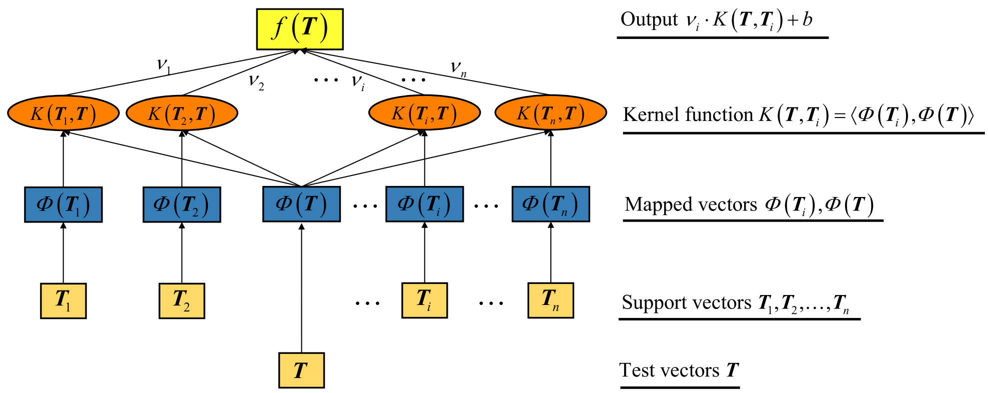


Fig. 14 A schematic presentation of SVR for separate the temperature-induced responses [40]

kernel function, so that the temperature influence part $\hat{Y}$ can be effectively separated in the structural response Y later.

In theory, SVM can predict better than RA method, but the difference depends on the nonlinear degree of the relationship between the temperature and response. Ni et al. [40] addressed a SVM model of the temperature effect on modal frequencies of Ting Kau Bridge, and compared the results of SVM model with that of MLR model, which showed that the SVR model can map modal frequencies better according to temperature. Jang and Smyth [67] also compared the prediction results of temperature-induced natural frequencies between MLR and three machine learning methods (SVM, ANN and random forests), which indicated that the predicted results of machine learning methods have not been significantly improved, since the degree of nonlinearity between the natural frequency and temperature distribution is relatively low. Kromanis et al. [69] developed a SVM model to predict the thermal strain of bridges from distributed temperature measurements, and in his later study [70], the performance of various models of establishing the temperature-induced strain relationship are compared, such as MLR, SVM, ANN and robust regression, which showed that all of the above methods can produce accurate results.

3.1.3 ANN

Another input and output method has been developed with ANN, due to its strong capability to approximate the nonlinear functions between inputs and outputs through learning from historical data. The basic principle of predicting the structural response $\boldsymbol{Y} = [Y_1, Y_2, \ldots, Y_i, \ldots, Y_q]^{\mathrm{T}}$ with an ANN model is shown in Fig. 15, the ANN of the nonlinear relationship between input $\boldsymbol{T}$ and output $\hat{\boldsymbol{Y}}$ can be described as,

$$\hat{\boldsymbol{Y}} = \psi(\boldsymbol{T}) \tag{13}$$

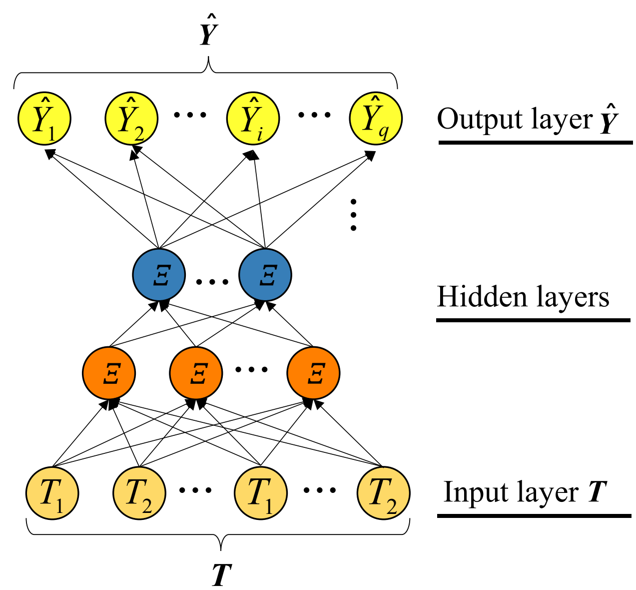


Fig. 15 A schematic presentation of ANN for separate the temperature-induced responses

Training the ANN model with monitoring data from undamaged structures, the temperature-induced part of the response $\hat{\boldsymbol{Y}}$ can be effectively separated from the total response $\boldsymbol{Y}$ later.

Zhou et al. [71] used the back propagation neural network (BPNN) to establish a correlation model between damage sensitive modal features and temperature, and normalize modal features at different temperature conditions to an identical reference status of temperature, and the proposed approach was examined in the instrumented Ting Kau bridge. BPNN may suffer from slow convergence and cannot give the confidence intervals of the predictions, to overcome these drawbacks, Jin et al. [72] established a neural network model trained by extended Kalman filter (EKFNN) to eliminate temperature effect of natural frequency.

3.1.4 Other input and output methods

In addition to the methods described above, some other input (temperature)-output (structure response) statistical methods have also been proposed. For example, autoregressive model with an exogenous input (ARX). Peeters et al. [28] trained an ARX to predict natural frequencies using temperature data as the exogenous data, and use this method to assess the future damage of the Z24 Bridge. To obtain a better fitting model of the relationship between the natural frequency of Dowling Hall footbridge and temperature, Moser and Moaveni [34] compared the analysis results of the ARX method with other RA, and found that the fit result of 4-order regression model is better than ARX. Wang et al. [73] compared the prediction accuracy of the LR and ARX for temperature and frequencies correlation, which found that the precision of the ARX model was better than that of the LR. Noted that all the above results are data-specific, so the reproducibility needs to be verified. Jang and Smyth [67] tried to establish the correlation between temperature and natural frequencies using random forests method to predict the vibration characteristics of bridge.

3.2 Output-only methods

3.2.1 PCA

PCA is a multivariate statistical analysis method, which has a basic idea of reducing dimensions, that is, on the premise of ensuring less loss of original data information, transforming high-dimensional related variables into low-dimensional unrelated variables. The new variables retain the most information of the original variables, which are known as the principal components (PCs) of original variables. PCA considers the temperature effect as hidden variables, taking the simplest two-dimensional data as an example, the temperature-induced response separation process using PCA is shown in Fig. 16 [74], considering that the temperature-induced part is the main influencing factor of the structural response, that is, the first-order principal component of the structural response is the temperature-induced part (PC1), and the PC1 is extracted by singular value decomposition of a covariance matrix of the features from the original matrix Y (composed of the structural response).The environmental-factor characterized space (known as scores matrix) can be obtained by projecting the original matrix Y onto the first-order principal component transformation matrix P_1:

$$\hat{X} = P_1 Y \tag{14}$$

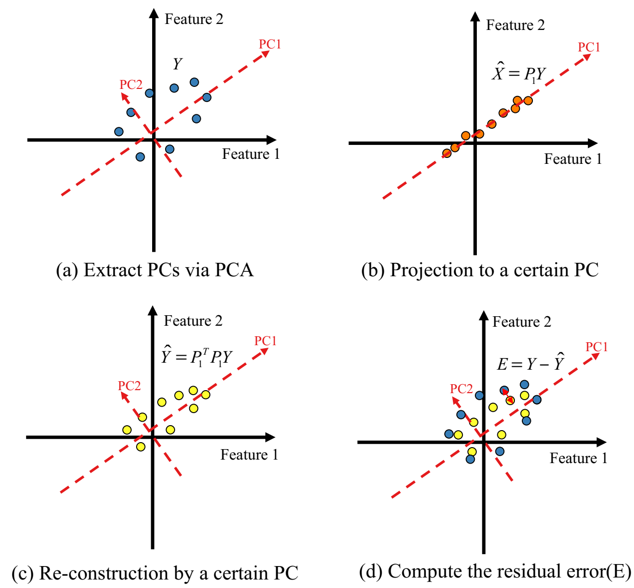


Fig. 16 A schematic presentation of PCA for separate the temperature-induced responses (two-dimensional example) [74]

then the new data can be re-mapped into the original axes with the opposing transformation P_1^{T}:

$$\hat{Y} = P_1^{\mathrm{T}} P_1 Y \tag{15}$$

Kullaa [7] embedded environmental factors as damage variables in the damage characteristic parameters, PCA is used to eliminate the influence of environmental factors on the damage characteristic parameters. Yan et al. [20] proposed a linear method based on PCA to eliminate the effect of temperature on the natural frequency, and further Yan et al. [75] discussed an extension of the method to handle non-linear cases, which can be encountered in some complex structures. Kromanis et al. [76, 77] proposed to use PCA to extract the temperature-induced component of strain response in the pre-processing of strain monitoring data. Wah et al. [78] used the PCA method to distinguish the effects of damage and of the changing temperature conditions on damage sensitivity features. Xu et al. [79] established a residual strain energy method to locate the damage of 3D structures under temperature variations, which employed the residual mode shapes by PCA to construct the damage localisation indicator.

Although the conventional PCA (linear PCA, LPCA) method is widely used to separate TIR, due to the complex nonlinear characteristics of the actual monitoring data, the method cannot achieve good results in some cases. To separate complex environmental effects more effectively, some nonlinear PCA (NLPCA) methods have been proposed in recent years. Jin et al. [74, 80] proposed a novel adaptive PCA to consider varying environmental conditions (i.e., both stationary and non-stationary conditions), which enables to capture the intrinsic system behaviour by continuously updating the reference model before detecting damage. Lim et al. [81] developed a data normalization method using Kernel PCA to improve the ability of damage detection under varying temperature and external loading conditions, which achieved good results in the detection of bolt looseness.

3.2.2 Auto-associative neural network (AANN)

AANN is a special ANN structure with the same input and output layer, which is usually used to simulate the NLPCA process [82] and solve the problems of feature extraction, dimensional reduction and pattern recognition of high-dimensional spatial data. The temperature effect separation process of the structural response $\boldsymbol{Y}$ using AANN model is shown in Fig. 17. This network consists of five layers: input layer, hidden layer (mapping layer, "bottleneck" layer, de-mapping layer) and output layer. The "bottleneck" layer has a small number of neurons. When the input data (structural response $\boldsymbol{Y}$) transmitted to the "bottleneck" layer during the training process, most representative feature of the multi-dimensional input data, that is, the temperature-induced response part is extracted. Then the data are reconstructed through the de-mapping layer to obtain $\hat{\boldsymbol{Y}}$ that retains the main features of the data. The de-mapping layer and the mapping layer respectively represent the nonlinear relationship between the input layer to the "bottleneck" layer and the "bottleneck" layer to the output layer, which can be expressed as:

$$\boldsymbol{T} = \varphi(\boldsymbol{Y}) \tag{16}$$

$$\hat{\boldsymbol{Y}} = \psi(\boldsymbol{T}) \tag{17}$$

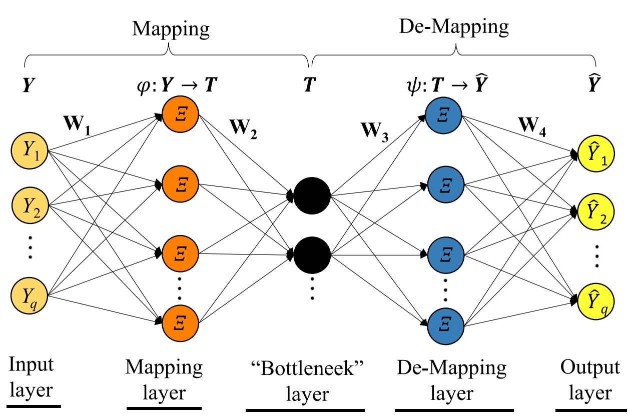


Fig. 17 A schematic presentation of AANN for separate the temperature-induced responses [24]

Ko et al. [83, 84] used a series of structural natural frequencies under healthy and damaged conditions as the inputs of AANN, and reduced the uncertainty in environmental conditions. Sohn et al. [85] extracted the damage-sensitive features by a linear prediction model combining autoregressive and autoregressive with exogenous inputs models (AR-ARX), input the damage-sensitive features to the AANN, and separated the temperature response part of the extracted damage feature change. Hsu et al. [86] utilized AANN to extract potential environmental factors in the stiffness of structural components. Gu et al. [24] took temperature as a potential effect factor of modal frequencies, and used the natural frequencies in the undamaged condition to train the AANN to establish the potential mapping relationship between temperature and natural frequency, thereby eliminating the effect of temperature change. Zhang et al. [87] constructed the damage features by time series analysis, and extracted the damage features of undamaged structures under different temperatures for training AANN, thus effectively eliminating the effect of temperature in damage identification. Ye et al. [88] proposed an AANN-SVR model to interpret the relation between environmental factors (e.g., temperature, wind speed, and wind direction) and natural frequencies. In their study, AANN was used to eliminate the high correlation between environmental factors and extract nonlinear principal components, and then SVR model was used for prediction.

3.2.3 Empirical mode decomposition (EMD)

EMD is a significant time–frequency analysis method for analysing nonlinear and non-stationary signals. The essence is to decompose the original signal into several sets of intrinsic mode function (IMF) [89]. A signal is separated into a sum of intrinsic mode functions $I_i(t)$ and a margin $r_n(t)$ by EMD, and the order of the $I_i(t)$ separated from the original signal corresponds to the frequency of the signal from low to high. The frequency of the margin $r_n(t)$ is the lowest which is the trend component in the signal:

$$Y(t) = \sum_{i=1}^{n} I_i(t) + r_n(t) \tag{18}$$

Unlike other high-frequency loads, the frequency of the temperature effect is lower in the overall response. Therefore, to separate temperature effects with EMD, it is generally assumed that the low-frequency component in $I_i(t)$ or margin $r_n(t)$ is mainly composed of the temperature effect part of the response. So that the temperature effect can be separated from the total. Wu et al. [90] established a rapidly convergent EMD method to more efficiently decompose the effective temperature and cable force signals for possible applications in the SHM of cable-stayed bridges.

The IMF obtained by EMD is often modal mixed, ensemble empirical mode decomposition (EEMD) is an improved EMD method, which can solve this problem well. Xia et al. [56] used EEMD to separate the temperature-induced strain from measured strain responses. Zhu et al. [91] proposed a temperature-induced extraction method, which combined mode decomposition, data reduction, and blind separation. For mode decomposition, EMD and EEMD were performed, followed by PCA is used to data reduction. Then independent component analysis (ICA) for blind separation was used. It enabled the extraction of temperature-induced responses from the mixed structural response without the need for any previous loading conditions and information on the structural physical model.

3.2.4 Other output-only methods

For output-only methods, in addition to PCA, AANN, and EMD, other important methods are also used to predict and separate TIR, e.g., wavelet method, autoregressive analysis and Bayesian method, etc. Ni et al. [92] presented a wavelet solution analysis method that can effectively separate and extract temperature-induced and traffic-induced parts from the measurement strain. Wu et al. [93] used wavelet transform to extract the temperature change component with higher cut-off frequency in the strain data. Xu et al. [52] proposed an application based on the multi-resolution wavelet method, which extracts thermal effects from the bridge response based on the distinguished frequency bandwidths. Wang et al. [94] developed an improved Bayesian dynamic linear model to forecast the temperature-induced strain, which considers an autoregressive component in addition to the trend, seasonal and regression components. Liang et al. [25] proposed a co-integration analysis method to filter the temperature effect in frequency. Erazo et al. [95] elaborated a Kalman filtering method which can decouple dynamic characteristics changes caused by structural damage and varying environmental conditions.

3.3 Summary

Summing up the above methods mentioned, the main idea of input & output method is to establish the relationship model between temperature and structural responses, and use the model to separate and forecast the further responses with the future monitoring temperature data. RA methods (e.g., LR, MRA, RMLR, MPR etc.) are simple and feasible, more importantly, the analysis results can be expressed by explicit formulas, but the separation effect of the non-linear condition is poor. Compared with RA, SVM and ANN methods are not usually easy fall into local minimum problems, which can theoretically approximate arbitrary functions with arbitrary accuracy, therefore the non-linear relationship between temperature and responses can be determined accurately. But both SVM and ANN are black box models which means that they have no explicit formulas of the modelling results. In addition, since the input parameters of these input and output models (e.g., RA, SVM, ANN, ARX etc.) are only temperature data, to ensure accuracy in the separation and prediction of further, the responses data of the model training should be less affected by other loads except the temperature, and the under-fitting and over-fitting problem also needs to be noted.

The basic idea of the output-only method is that the measure environmental parameters are not needed, because they are taken into account as embedded variables. In the PCA method, the number of principal components of the responses is implicitly assumed to correspond to the number of independent environmental factors, that is, it can separate the structural responses under the effect of many environmental factors (e.g., temperature, wind speed, etc.). However, PCA can only analyse the current responses while it cannot predict future responses, and the ability to deal with complex nonlinear environmental effects also needs to be further improved. AANN can analyse the data by NLPCA, and the trained neural network model can also use to forecast the future data, but selecting the network topology structure is needed. EMD and wavelet analysis are signal analysis methods, which can separate the different periodicity and trend temperature-induced part from the overall response data. But those signal analysis methods are suitable for the analysis of time series response data of a certain sampling frequencies, thus are not usually used to analyse static data of low frequency sampling. The probabilistic methods (e.g., the Bayesian method) have good prospect, which can quantify the uncertainty of the environmental factors of the data. Furthermore, in addition to temperature effects, the response data of the on-site monitoring system will also be affected by other environmental and load factors, which are very complex. In the process of temperature-induced response separation or prediction, the above methods can be used in combination to take advantages of them.

4 Damage assessment considering temperature effects

Section 3 introduced the different methods for forecasting and separating TIR, from the perspective of health monitoring, the ultimate purpose of these methods is to identify structural damage and evaluate its safety under the combined effects of environmental temperature factors effectively. In this section, the research frameworks of damage assessment considering temperature effects that integrates various methods in recent years have been introduced. Corresponding to the Sect. 2, those methods are organized into two categories, that is, vibration-based methods and static-based methods according to the type of monitoring data.

4.1 Vibration-based methods

As mentioned in Sect. 2.1, the idea of vibration-based damage detection is to identify the changes of dynamic characteristics Y (e.g., natural frequencies, mode shapes, etc.) based on the monitoring data. But as a simple beam depicted in Fig. 18, these dynamic parameters are sensitive to both structural damage and temperature, that is, the change in dynamic characteristics $Y^{\mathrm{D}}_{\delta T}$, is a superposition of damage-induced part Y^{D} and temperature-induced part $Y_{\delta T}$, and damage may not be detectable under ambient temperature changes. Therefore, the variability of dynamic characteristics caused by temperature effect must be eliminated so that the detection of the actual changes by the damage can be found. According to whether finite element model (FEM) are used in the process or not, these existing vibration-based methods can be classified as model-based methods and data-driven methods.

In the model-based method, the structural parameters (here, i.e., damage criteria) are iteratively adjusted to minimize the difference between the calculated response of the numerical model and the measured response of the actual monitoring structure, so as to realize the updating of the FEM of the structural state. In this way, the updated FEM can be used as a baseline to detect the damage of the structure. In view of the important influence of the environment on structural response, it is reasonable to take temperature effect and damage criteria as updated structural parameters at the same time [15]. Hence, the stiffness matrix of the structure depends on the damage factors and the temperature [22]:

$$K^{\mathrm{D}}_{\delta T}(\beta, T) = \sum_{i} \left(1 - \beta_i\right) k_i\left(T_i\right) \tag{19}$$

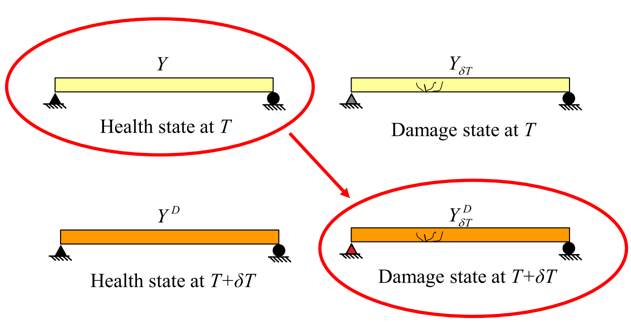


Fig. 18 Changes of modal characteristics due to damage (D) and temperature-change (δT) [31]

where $K^{\mathrm{D}}_{\delta T}$ is the stiffness matrix of the damaged structure under varying temperature, $k_i\left(T_i\right)$ is the stiffness matrix of the ith element at temperature T_i, and β_i is the damage factors of the ith element, which is represented here as a element stiffness reduction. Since the temperature impacts has been embedded in the updated parameters, the model-based methods do not need to remove the temperature effect, and can locate and identify the damage degree from the global perspective [96]. Meruane et al. [22] proposed a model-based damage detection methods to distinguish the temperature effects and real damage events, and the efficiency of the method is verified by the simulated data of a three-span bridge and experimental data of the I-40 Bridge. To avoid the non convergence and local minimum in the optimization process, some model-based methods combine global optimization algorithm, such as genetic algorithm (GA) [26], particle swarm optimization (PSO) [73] and particle swarm optimization-cuckoo search (PSO-CS) [27] with some novel objective response functions, which have been proved to be efficient in the location and severity identification of structural damage under the influence of temperature variation and noise.

Different from the model-based method, the data-driven method does not resort to the structural numerical model, but simply relies on the collected monitoring data to explain the structural behavior. With the help of machine learning algorithm, it is the most widespread and expected to achieve long-term continuous monitoring. In conclusion, the data-driven Damage assessment process considering temperature change can be roughly divided into three parts: feature extraction, temperature effect filtering and damage decision. For feature extraction, damage sensitive features (DSFs) are usually constructed directly by frequency domain parameters (such as natural frequency and mode shape) obtained from modal analysis [31], and some novel DSFs constructed by modal parameters have also been studied, such as modal strain energy [79], mode shape curvatures [97]. In addition, some DSFs extracted by time-domain analysis are also proposed recently [87, 98]. In terms of temperature effect filtering, PCA including LPCA and NPCA (such as AANN) are more commonly used, some other filtering methods have also been proposed in recent years [95]. Additionally, exploring some DSFs that are sensitive to damage but not sensitive to environmental changes provide new ideas for environmental impacts filtering, such as the frequency ratios proposed by Surace et al. [99]. For damage decision, the most commonly way is distinguish the damage directly based on the residual of DSFs (or damage indicators, DIs) filtering out the temperature effect. In addition, the methods of Euclidean distance [24], Mahalanobis distance [100] and control chart [21] are also often used in the damage decision-making process. A clearer comparison of some current damage assessment frameworks is shown in Table 3. The last three columns show the decision-making ability of these frameworks, I, II and III represent three levels, which are damage alarm, damage location and damage quantification, respectively.

4.2 Static-based methods

A multitude of damage assessment frameworks have been employed based on the static responses under varying temperature. In short, there are two different approaches to handling temperature effects in these processes, as shown in Fig. 19. The first approach is similar to vibration-based monitoring methods, where temperature is considered as an adverse effect during the monitoring progress, which is likely to cover the changes in the responses caused by other external loads, thereby causing false negative or false positive results of damage identification and safety assessment. Therefore, the temperature-induced part should be removed in the monitoring static responses. Based on the normalized displacement after removing the temperature effect, Ding et al. [11] evaluated the damage of the expansion joint of the cable-stayed bridge effectively.

The second approach is considered to offer more promise. Because the temperature effect of structure is no less than other external loads in some cases, temperature-induced static responses should be reflected rather than eliminated. Since temperature-induced static responses are typically substantial and relatively easy to measure, the health monitoring process can be performed by directly analysing the changes in temperature-induced responses. Similar to Sect. 4.1, depending on whether to rely on numerical models in the process, these methods can be divided into model-based methods and data-driven methods.

Since the main work of the model-based method is to update and identify structural model parameters, it is also called structure identification (St-Id). As is shown in Eqs. (6) and (7), temperature-induced responses are highly sensitive to structural stiffness and boundary stiffness, therefore, temperature can be used as a favorable driving load for St-Id. Kulprapha et al. [102] proposed a method to monitor the structural health of multi-span concrete bridges using their ambient thermal loads and responses, and an numerical model was developed to diagnose damage in further studies. Yarnold et al. [47] proposed a temperature-based structure identification (TBSI) and structure health monitoring (TBSHM) process (Fig. 20) based on the responses under temperature loading, and applied it to the monitoring of several bridge structures successfully [48, 50]. For TBSI and TBSHM, the measured values are just temperature, temperature gradient, strain and displacement, linear or non-linear analysis of the measured input and response based on the

Table 3 A summary of vibration-based data-driven damage assessment frameworks proposed recently

Proposed by	Method			DSF	Decision-making ability		
	Feature extraction	Temperature effect filtering	damage decision		I	II	III
Kim et al. [31]	Modal analysis	LR	Control chart	Natural frequencies	√		
Deraemaeker et al. [21]	Spectrum analysis	PCA	Shewhart-T control charts	Peak indicators of spectrum	√		
Jin et al. [74, 80]	Modal analysis	Adaptive PCA	Euclidean distance	Natural frequencies	√		
Gu et al. [24]	Modal analysis	AANN	Euclidean distance	Natural frequencies	√		
Kostic and Gul [98]	Time series analysis using ARX	ANN	Residual-based	Fit ratio of ARX	√	√	
Xu et al. [79]	Modal analysis	PCA	DIs constructed with residual	Residual strain energy	√	√	
Shokrani et al. [97]	Modal analysis	PCA	DIs constructed with residual	Mode shape curvatures	√	√	
Zhang et al. [87]	Time series analysis using ARX	AANN	Residual-based	Fit ratio of ARX	√	√	
Erazo et al. [95]	Spectrum analysis	Kalman filtering	Residual-based	peak indicators of spectral density	√		
Kumar et al. [100]	Time series analysis using PCA	PCA	Mahalanobis distance, X-bar control chart	PCs of acceleration series	√		
Sarmadi et al. [101]	Modal analysis	kNN	kNN, generalized extreme value, block maxima	Mahalanobis-squared distance of test frequencies	√		

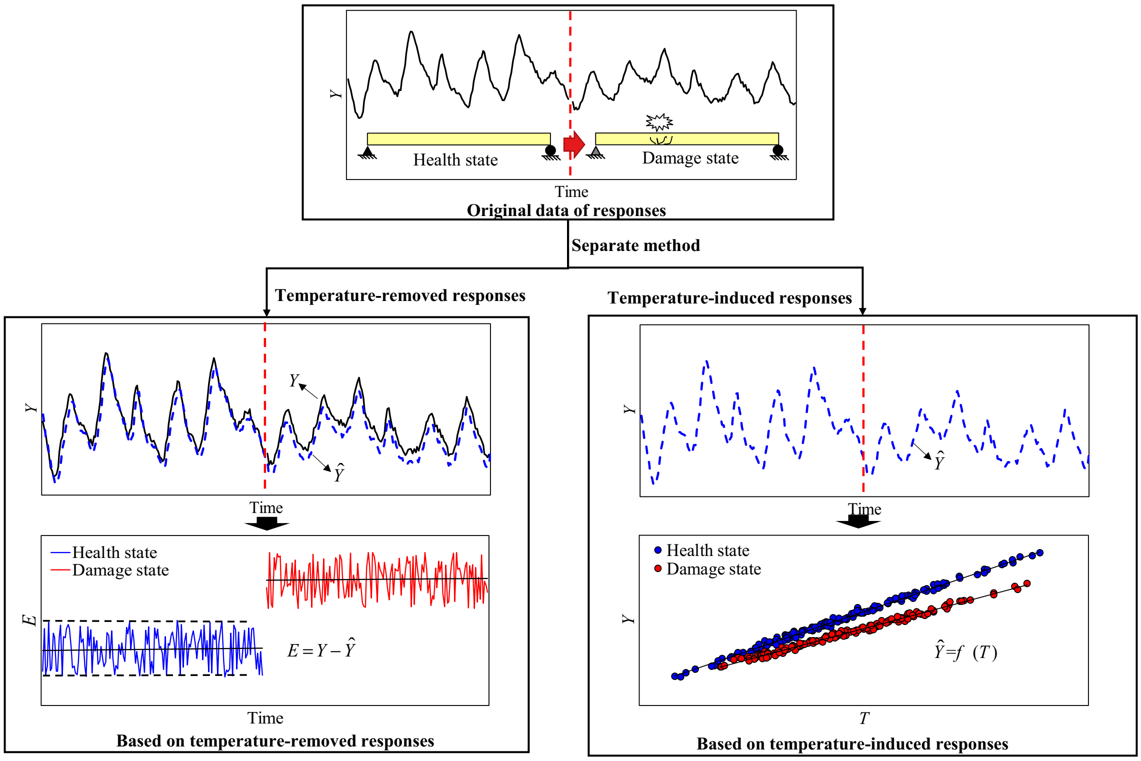


Fig. 19 Two different approaches to handling temperature effects based on the static responses

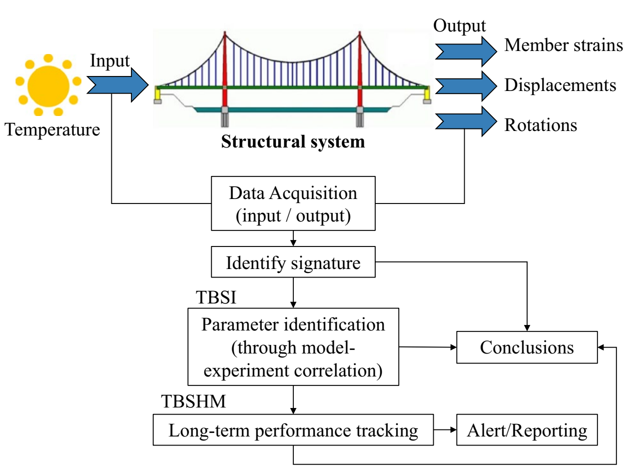


Fig. 20 TBSI and TBSHM process [47]

characteristics of the observed values and the final target of the St-Id, and finally the prior finite element model is updated. Under the traditional St-Id framework, TBSI has innovated and developed its prior model and experimental steps, making it possible to assess the structural safety based on temperature-induced responses. Lyu et al. [51] used TBSI to identify the connection stiffness of historic timber buildings. Jesus et al. [103, 104] applied a modular Bayesian method for St-ID of a reduced-scale aluminium bridge model subjected to thermal loading.

Data-driven methods based on temperature-induced static responses have also received attention in recent years. Kromanis et al. [70, 76, 77] proposed a temperature-based measurement interpretation (TB-MI) framework to detect anomaly of structure. TB-MI method can be implemented using a data-driven strategy to generate statistical models that can accurately predict the thermal response, given a reference set of measurements. Compared with model-based method, this method can be applied to other structures after fine-tuning or without modification, and has advantages when large amounts of data from continuous monitoring are processed. The framework includes two key steps (Fig. 21): first, predict the thermal effects of the structure through a regression-based thermal response prediction (RBTRP) method which can build a model that predicts thermal response values by calculation. Then, analyse the differences between the predicted results and the subsequent measured results to identify structural anomalies. Zhu et al. [105] presented an anomaly detection method, called temperature-driven moving principal component analysis method, designated as Td-MPCA, which introduced the idea of blind source separation (BSS) for thermal identification with intent to enhance the performance of moving principal component analysis for anomaly detection, see Fig. 22 for details.

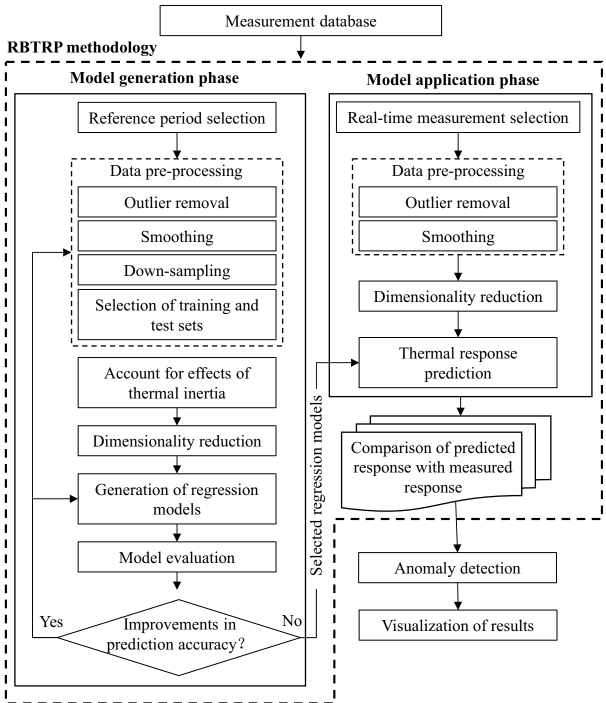


Fig. 21 The TB-MI approach incorporating the RBTRP methodology [70]

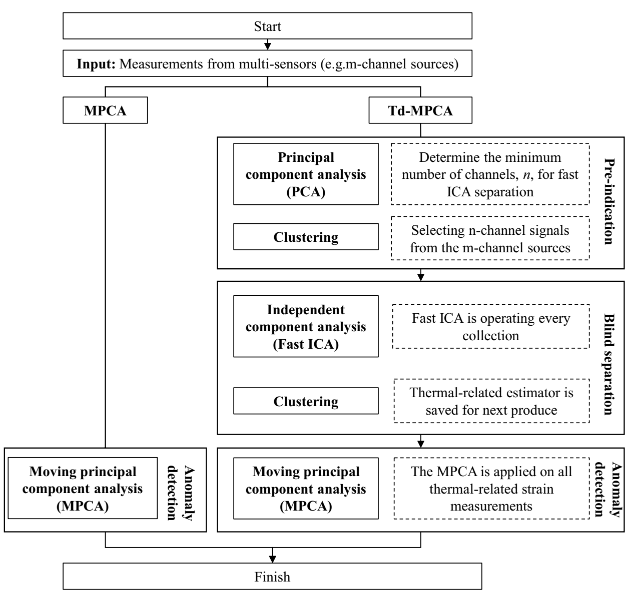


Fig. 22 Flowchart of MPCA and proposed Td-MPCA for anomaly detection [105]

4.3 Summary

In this section, damage assessment frameworks considering temperature effects are classified and introduced. As everything has two sides, these methods also have their own strengths and drawbacks, as shown in Table 4. To obtain better damage decision-making, future research should devote to improving these drawbacks, and combination methods should be proposed to solve the actual SHM system problems.

5 Conclusions

This paper presents a comprehensive review on the recent development of SHM under varying temperature. The goal is to help broaden the study of health monitoring under consideration of environmental uncertainty. Conclusions of the work is as follows:

1. Most of the correlation researches of modal parameters and temperature are focusing on changes in natural frequencies of bridge structures, while less researches on other structural forms such as large venues and high-rise buildings. In addition, due to the influence of modal test accuracy, few studies concerning the correlation between other modal parameters (vibration modes and damping) and temperature. With the continuous development of methods of sensor layout optimization and modal analysis, these problems should be solved in future research. For static responses, the main researches focuses on the strain responses of bridges, with some studies on variations in displacement, deflection and tilting angle and other types of structures. Future researches about the correlation of structural measuring static responses and temperature need to pay more attention to the mechanism of temperature effects of the structures, so that the relationship between temperature and responses can be better established. Moreover, due to the complexity of the spatial distribution of the structure and the sunshine factor, the non-uniform temperature field also has significant effect on the structural responses, due to the complexity of the mechanism of thermal environment, there are currently little literatures on this issue, and further research is still needed in the future.
2. The separation and forecast methods of the temperature-induced part of the structural response data are commented, and the benefits and drawbacks of these methods have also been discussed. Many of these current methods only consider a single environmental effect such as temperature. Monitored responses usually include the impact of other environmental loads, such as wind, vehicle load, humidity, and complex noise interference, with the big data from field monitoring, the continuous improvement of the combination of some new machine learning algorithms to deal with multiple environmental factors is the future development trend. Furthermore, considering the complexity and uncer-

Table 4 Strengths and drawbacks of the damage assessment methods considering temperature effects

Method			Strengths	Drawbacks
Vibration-based	Model-based		1. Temperature is embedded in FEM as a potential factor, no need to filter temperature effect 2. Damage can be located and quantified 3. Easier to achieve global optimization of the model than Static-Based St-Id	The modelling errors and uncertainties make it face challenges in actual structural applications
	Data driven		1. Multiple dynamic characteristics can be extracted as DIs 2. Temperature effects can be filtered better by various methods 3. Real-time alarming is expected	1. Difficult to locate and quantify the damage 2. Difficult to explain the damage mechanism
Static-based	Based on temperature-removed responses		Analysing the influence of other factors (traffic load, etc.) on the structure except temperature more efficiently	The responses that removes the temperature-induced part may lose important information
	Based on temperature-induced responses	St-Id	1. Temperature can be used as a natural external excitation to St-Id 2. Compared with vibration-based St-Id, the amount of the data storage and the analysis process are simple	1. Uniform temperature field makes it difficult to accurately obtain model input 2. The non-linear relationship between temperature responses and structural parameters make the model uncertainty
		Data driven	1. Daily information motivated by environmental changes is fully utilized 2. Real-time alarming is expected	1. Accurate extraction of the temperature induced part is difficult 2. The sensitivity of temperature-induced responses to damage remains to be studied

tainty of site environmental factors, the probability methods should be paid more attention in the future.

3. For damage assessment, most of vibration-based processes are employed based on residuals after removing temperature effects, which are combined with statistical theory and hypothetical test to detect whether damage has occurred, more techniques for damage location and damage degree identification under variable temperature effects should be developed in the future. For static-based methods, the research framework based on the temperature-induced responses offer more promise, which treats temperature as a measurable excitation to establish a complete transfer function. In addition, most of the existing damage detection methods are deterministic methods, that is, the materials and working conditions of the damage detection structure are completely determined and known, but in fact, the true state of the structure is difficult to determine and obtain accurately. From this perspective, later test data for statistical probability analysis are used to correct this uncertain state of the structure.

Acknowledgements The authors express our appreciation for financial support by: the Specialized Research Fund of the National Nature Science Foundation of China (no. 51525803), the Joint Funds of the National Natural Science Foundation of China (U1939208), Overseas Expertise Introduction Project for Discipline Innovation (B20039).

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