

Simulation and prediction of water temperature in a water transfer channel during winter periods using a new approach based on the wavelet noise reduction-deep learning method

Tiejie Cheng¹, Jun Wang¹, Jueyi Sui^{2*}, Feihu Song¹, Hui Fu³, Tao Wang³, Xinlei Guo³

¹ School of Civil Engineering, Hefei University of Technology, 193 Tunxi Road, Hefei, Anhui, China.

² School of Engineering, University of Northern British Columbia, 3333 University Way, Prince George, BC, Canada.

³ State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing, China.

* Corresponding author. E-mail: jueyi.sui@unbc.ca

Abstract: In winter, the water transfer channel of the Middle Route of South-to-North Water Transfer Project (MR-StNWTP) in China always encounters ice problems. The precisely simulation and prediction of water temperature is essential for analyzing the ice condition, which is important for the safety control of the water transfer channel in winter. Due to the difference of specific heat between water and air, when the air temperature rises and falls dramatically, the range of change of water temperature is relatively small and has a lag, which often affects the accuracy of simulation and prediction of water temperature based on air temperature. In the present study, a new approach for simulating and predicting water temperature in water transfer channels in winter has been proposed. By coupling the neural network theory to equations describing water temperature, a model has been developed for predicting water temperature. The temperature data of prototype observations in winter are preprocessed through the wavelet decomposition and noise reduction. Then, the wavelet soft threshold denoising method is used to eliminate the fluctuation of certain temperature data of prototype observations, and the corresponding water temperature is calculated afterward. Compared to calculation results using both general neural network and multiple regression approaches, the calculation results using the proposed model agree well with those of prototype measurements and can effectively improve the accuracy of prediction of water temperature.

Keywords: Neural network; Water transfer project; Water temperature; Wavelet noise reduction.

1 INTRODUCTION

Spatially and temporally, water resources distribute uneven in the world. The long-distance water transfer project is one of the common approaches to effectively solve the water shortage problem (Choi et al., 2020; Karandish et al., 2021). The main canal of the Middle Route of South-to-North Water Transfer Project (MR-StNWTP) in China is about 1267 km long, which belongs to the long-distance cross-basin water transfer project (Yang et al., 2022). In winter, water is transferred along the MR-StNWTP from the warm zone in South China to the semi-cold region in North China. Both air temperature and water temperature along the channel decrease gradually. With the decrease in temperature in winter, serious safety issues along the water transfer channel often arises due to the presence of ice in the channel (Kuppel et al., 2017; Zhong et al., 2019). The presence of a cover on water surface leads to the change of turbulent kinetic energy, and the shift of the maximum flow velocity toward the channel bed and thus intensified the deformation of the channel (Jafari and Sui, 2021; Namaee and Sui, 2019, 2020; Sui et al., 2000, 2009, 2010). Under an ice-jammed flow condition, it will cause a significant deformation of the channel and increase in water level (Sui et al., 2002, 2005; Yang et al., 2019). Results showed that water temperature is an important factor affecting the generation of frazil ice in water, development of floating ice pans on water surface and formation of ice cover in channels or rivers (Huang et al., 2019; Sui et al., 2008). Since water temperature is also a comprehensive indicator for describing the effects of air temperature, solar radiation,

boundary heat transfer and hydraulic conditions on water bodies (Elnashar et al., 2023; Sharma et al., 2019), the prediction of water temperature is essential for the forecast of ice regime in channels or rivers (Yao et al., 1959). Under an ice-covered flow condition, the formation and development of ice jams (or dams) in water transfer channels should be minimized in order to avoid ice flooding. Obviously, one should better understand the characteristics of water temperature in water transfer channels as well as air temperature in the study region, and thus water temperature can be controlled for preventing water transfer channels from flooding.

Haeuser et al. (1980) derived the equation for heat transfer through water temperature convection based on the conservation principle of mass and heat energy in Eulerian form. In their study, the surface heat transfer and turbulence effects have been considered, and the mathematical characteristics and solution method of the equation have been summarized. By comparing the simulation results to those of field measurements along the Lower Eibe River, it was found that their proposed program had certain applicability in prediction of the water temperature. Based on the conservation of thermal energy, Yearsley (2009) used the Euler-Lagrange mixed numerical scheme to solve the time-varying equation of river water temperature. The calculation efficiency and accuracy by using the numerical scheme has been verified by field observations of river water temperature. The numerical scheme utilizes the advantages of the Lagrangian reference frame and has the features of high efficiency and accuracy compared to the previous regional scale for calculating water temperature. Results showed that with the

increase in air temperature, the water temperature at the simulation site also increases. To investigate the water resource management issue for a long-distance water transfer system, Liu et al. (2021) developed a numerical simulation system for water transfer under an ice-covered flow condition. They claimed that there is uncertainty in the calculation approaches and mathematical models for assessing the hydraulic response of channel under an ice-covered flow condition. They pointed out that it is necessary to continuously carry out prototype observations of winter water temperature for calibrating parameters of numerical model. Turcotte et al. (2014) pointed out that the evolution of ice in canals is affected by water temperature conditions in the upstream reach and tributaries as well as river morphology. Results of field observations showed that different water temperatures and boundary conditions resulted in different ice regimes in rivers. In winter, even if the air temperature changes dramatically, the change in water temperature is normally much less than that of air temperature. Their study emphasized the interactions among water temperature and boundary conditions, hydraulic conditions, thermal conditions, and ice process.

In recent years, with the advancement in calculation technology, the deep-learning method based on statistical principles have been gradually developed (Chellali et al., 2016; Dargan et al., 2020). Wang et al. (2010) used the deep-learning method to develop a model for simulating the thickness of ice jam and water level during ice-jammed period. Their model has been verified using data of field measurements and can be used to predict the thickness of ice jam and water level. They also pointed out that results of prediction using both neural network method and support vector machine method have a superior accuracy comparing to those using the multiple regression method. Saadatpour et al. (2017) used a neural network coupled evolution algorithm instead of the simulation model of computational fluid dynamics to simulate the downstream water temperature, water demand and power generation during the operation of a reservoir. Results showed that the neural network model can better simulate the temperature of water released from the reservoir and water temperature in the downstream river. Fu

and Yao (2015) identified the correlation between the climate model and river-breakup date by introducing the multi-resolution analysis method for extracting the nonlinear trend. Their results show that the river-breakup date is closely related to air temperature and snow cover on the ground, which indicates the effectiveness of the wavelet analysis method in pattern recognition. Lafrenière and Sharp (2003) pointed out that wavelet analysis is a fast and effective means to characterize runoff, temperature and precipitation, as well as their relationship and interannual variations. It can effectively determine the interannual and seasonal variation of the relative contribution of different water sources to runoff, and the variation of time required for the passage of melted ice through the catchment. Renata et al. (2019) developed the wavelet transform and artificial neural network (WT-ANN) hybrid model for predicting daily water temperature in river by combining four wavelet bases, namely, Daubechies, Symlet, Meyer and Haar. They claimed that the WT-ANN hybrid model better can simulate and predict the time series of water temperature in rivers comparing to the linear, nonlinear and traditional neural network models. Based on the Levenberg-Marquardt algorithm, Wang et al. (2008) improved the back propagation (BP) neural network to predict the dates for water temperature to turn stable positive and stable negative. The above-mentioned methods are no longer completely limited to the complex numerical calculation of the relevant physical equations. For problems with unclear mechanism and unknown parameters, the above-mentioned methods show unique advantages.

By using the general physical equation to study the change of water temperature in rivers, Moore and Leach (2021) found that the heat flux was an important factor in controlling the change of water temperature. Generally, due to the complexity of boundary condition and environment aspects, the parameters in equations vary widely and become obvious uncertainty. Along the MR-StNWTP, as showed in Figure 1, it has been reported that ice jams/dams and other ice conditions occur often in winter (Cheng et al., 2022). Both the factors affecting water temperature and extent of influence vary in winter. During the simulation and prediction process of water temperature in winter, on the one

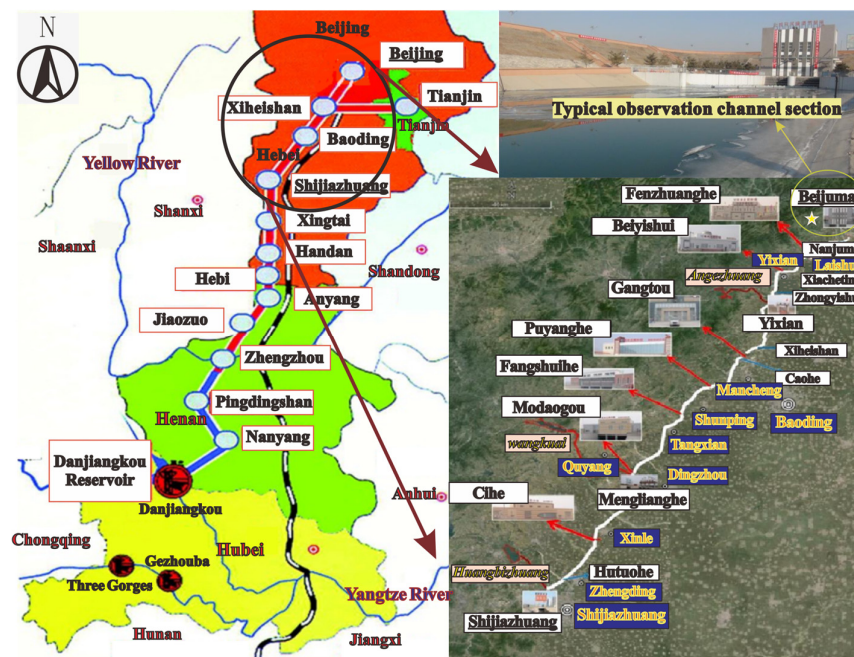


Fig. 1. Overview of study area.

hand, it is necessary to consider the physical principals reflected by equations describing water temperature; on the other hand, the deep-learning method can be used to calibrate the effect of heat transfer coefficient in those equations. Through such an approach, the generalization of a model can be enhanced. Furthermore, to constrain the solution under general physical equations, it has more practical significance.

Ice problem in water transfer crossing different watersheds involves multidisciplinary subjects (Cheng et al., 2022). The Beijuma River sluice gate of the MR-StNWTP is located at the northern end of the Beijing-Shijiazhuang cross section of the Middle Route, as shown in Figure 1. The Beijuma River sluice gate is the junction of the water transfer channel from the open channel to a culvert. The air temperature around this channel cross section is relatively low. Data of field measurements show that following ice conditions at the Beijuma River cross section may occur during winter periods: (1) decrease of water temperature (due to the air temperature) leads to the formation of ice pans floating on water surface, which is essential for the development of ice jams/dams; (2) the formation and development of ice pans floating on water surface, shore ice cover along channel bank, ice jam/dam in the channel may cause the damage of hydraulic structures. Therefore, the section around the Beijuma River sluice gate is selected as a typical cross section for studying the variation in the present study.

2 METHODOLOGY

The general equation for describing temperature of water in an open channel can be expressed as follows:

$$\frac{\partial}{\partial t}(\rho_w c_p A_w T_w) + \frac{\partial}{\partial x}(\rho_w c_p Q_w T_w) - \frac{\partial}{\partial x}\left(E_x \rho_w c_p A_w \frac{\partial T_w}{\partial x}\right) = q_v \quad (1)$$

where ρ_w is the mass density of water, c_p is the specific heat capacity of water, T_w is the water temperature, Q_w is the flow discharge, A_w is the flow cross-sectional area of the channel, E_x is the diffusion coefficient, q_v is the heat flux.

Field observations indicate that the water temperature along the study channel section in flow direction doesn't change much, and the diffusion term in Eq. (1) can be ignored. Assuming that the flow is incompressible when the specific heat capacity is consistent, Eq. (1) can be simplified by combining the continuity equation of the flow, and it can be solved by the basic computa-

tional fluid dynamics method. In addition, the main objective of simulation and prediction of water temperature in winter is to assess the ice production and ice accumulation process. Thus, the impact of the changes of air temperature on water temperature is the key task. The source term in Eq. (1) can be described as:

$$q_v = B_w (\varphi_{wa} + \varphi_R + \varphi_E) \quad (2)$$

where B_w is the width of channel water surface, φ_{wa} is the water-air heat flux, φ_R is radiation heat flux, φ_E is evaporation heat flux. Since φ_{wa} represents the heat change caused by the heat exchange formed by the difference between air temperature and water temperature, it can be represented as:

$$\varphi_{wa} = \varphi'_{wa} - h_{wa}(T_w - T_a) \quad (3)$$

where φ'_{wa} represents the water-air heat flux when the air temperature is the same as the water temperature, which can be approximately regarded as a constant in winter. h_{wa} is the water-air heat exchange coefficient which depends on the environmental conditions. It is an uncertain parameter in the model and plays an important role on the change of water temperature throughout the winter. The radiation heat flux (φ_R) includes shortwave radiation and longwave radiation, and its calculated value is affected by geographical location, time, temperature, cloud cover and relative humidity. The evaporation heat flux (φ_E) can be determined by using data of air temperature (latent heat of vaporization), wind speed, air pressure and humidity, as shown in Figure 2. When the required meteorological data are available, based on hydrological data collected along the channel of the MR-StNWTP in winter, the wavelet analysis method can be used to process these data acquired in the field. As a consequence, the changes of meteorological factors and water temperature as well as their correlation at the typical channel cross section of the MR-StNWTP can be studied.

The wavelet analysis is one of the breakthroughs in harmonic analysis. It retains the advantages of the Fourier analysis and has been essentially developed in theoretical analysis and practical application. The wavelet transform is used to localize the time-space frequency of the signals, and the function is gradually multi-scale refined by scaling and translation operations to automatically adapt to the requirements of time-frequency signal analysis.

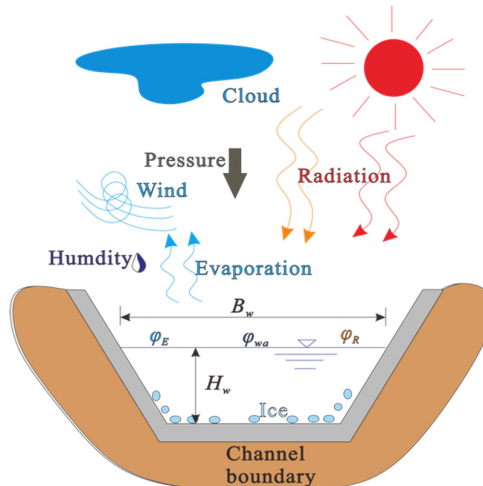


Fig. 2. Channel water heat budget diagram.

Define $\psi(t) \in L^2(R)$, when it satisfies the admissibility condition:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|}{|\omega|} d\omega < \infty \quad (4)$$

where $\psi(\omega)$ is the Fourier transform of $\psi(t)$. Then, $\psi(t)$ is called the base wavelet of $\psi(\omega)$. The wavelet function generated by $\psi(t)$ can be expressed as:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right) \quad (5)$$

where b is translation factor and a is scale factor.

Define $f(t) \in L^2(R)$, the continuous wavelet transform of its base wavelet function $\psi_{a,b}(t)$ is expressed as:

$$(W_\psi f)(a, b) = \int_{-\infty}^{+\infty} f(t) \overline{\psi_{a,b}(t)} dt \quad (6)$$

By expending a and b , spectrums of arbitrary precision at any instant can be determined. During the actual computation process, due to tremendous amount of data, parameters a and b can be discretized. Then, the discrete wavelets can be transformed. The corresponding function for the discretized wavelet can be expressed as:

$$\psi_{j,k}(t) = a_0^{-j/2} \psi(a_0^{-j}t - kb_0) \quad (7)$$

Here, Eq. (7) can be re-organized as:

$$f(t) = C \sum_{j=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} W_{j,k} \psi_{j,k}(t) \quad (8)$$

When cold waves enter a basin, the cooling intensity is high, and the air temperature gradually turns negative. The heat exchange between the air and water in the transfer channel results in the change of water temperature. The heat obtained by the water during the decrease of water temperature is less than the heat lost, and thus water temperature continues to decline. During the period of ice formation, the relationship between the change of air temperature and that of water temperature belongs to a strong nonlinear. The variations of air temperature and water temperature at some typical cross-sections during winter periods from 2015 to 2019 are shown in Figure 3.

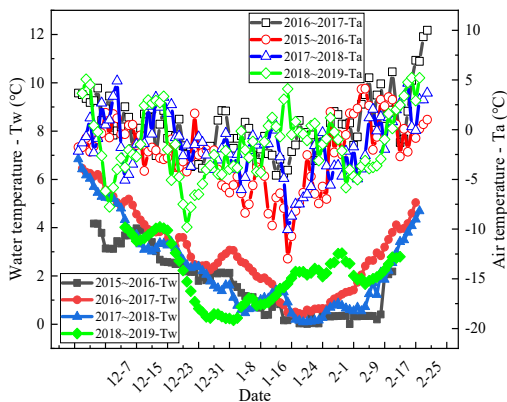


Fig. 3. Variations of air and water temperatures at some typical cross sections from 2015 to 2019.

One can see from Figure 3 that water temperature changes with air temperature. However, there is a certain delay. The air temperature changes frequently with a wider range, and the water temperature has a milder change comparing to that of air temperature. Also the change of water temperature in different years is similar. Due to very little variations of water level in each channel during the entire winter period, to study the effect of meteorological factors on water temperature, it is necessary to consider the continuous influence of air temperature on water temperature. Also, it should be also considered that the response of water temperature to air temperature is usually not instantaneous. Overall, the changes of frequency and amplitude of air temperature are much more than those of water temperature; and the change of water temperature lags behind that of air temperature.

In view of the above-mentioned aspects, the direct application of the simulated water temperature should result in unreasonable results. It is beneficial to improve the simulation accuracy by adopting relevant methods to reduce the noise of air temperature fluctuations and then simulating the variation of water temperature. The wavelet threshold denoising method can retain the signal coefficients and reduce most of the noise coefficients to zero. The basic process of applying the wavelet threshold denoising method can be summarized as follows:

1) Decomposition: after selecting the appropriate wavelet basis, the signals will be decomposed by multi-layer wavelet.

2) Action threshold: a threshold for the decomposed coefficients of each layer will be selected and apply a soft threshold to the high-frequency coefficients.

3) Reconstruction: after noise reduction, the wavelet coefficients will be used to reconstruct the original signal.

Under different thermodynamic and hydrodynamic conditions, the parameters in the model will change, which will affect the output of the model. Therefore, the neural network method is used to calibrate the parameters. The artificial neural network model is a mathematical equation that does not need to determine the mapping relationship between the input and output in advance. Through its own training and learning process, the results closest to the expected output value are obtained by providing the input value. The calculation process for this method is shown in Figure 4.

Eq. (1) describes the mechanism of changes of average water temperature from the perspective of energy conservation. The change of water temperature is affected by the previous temperature of water body, temperature of water in the upstream channel and meteorological conditions. Because of the formation of ice cover and the heat exchange between riverbed and water body in winter, there is a complex nonlinear relationship between water temperature and air temperature. Considering this aspect, the water-air heat exchange coefficient h_{wa} can be regarded as a more generalized parameter to reflect the heat exchange between air and water through different media. Therefore, by means of being coupled thermal process and hydraulic process, and though refined simulation of variation of water temperature in a channel, the prediction cycle and accuracy of water temperature can be improved. Eq. (3) can be changed as follows:

$$\varphi_{wa} = \varphi'_{wa} - f_{wa}(T_w - T_a) \quad (9)$$

where f_{wa} is the comprehensive heat exchange coefficient for the heat exchange between air and water body through different media such as river ice and channel bed. Since the formation of ice in a water body and the ground temperature in winter are also affected by many factors such as air temperature and cumulated temperature, the comprehensive heat exchange coefficient f_{wa} will be also affected by meteorological conditions, hydraulic

conditions, thermal conditions and other factors. Thus, the comprehensive heat exchange coefficient f_{wa} can be described as: $f_{wa} = f(T_{w-h}, T_{a-s}, T_i, v_w, v_{wind}, B_w, H_w, P, Ra, Rel, Rp, E, Hc)$, where: T_{w-h} represents the historical conditions of water temperature; T_{a-s} represents air temperature conditions including daily maximum, minimum, average and cumulated temperature during a period; T_i represents the time-effect factor. Since the annual variation of water temperature approximately shows a periodic pattern, the water temperature fluctuates around the average annual water temperature, the time-effect factor T_i can be reflected by both $\sin(2\pi T_{day}/T_{year})$ and $\cos(2\pi T_{day}/T_{year})$; where T_{day} is the date count of the year starting on January 1st (Note: January 1st is 1, and so on); and T_{year} is the number of annual dates; v_w and v_{wind} represent the components of the wind speed and the flow velocity in the flow direction, respectively, they have an important influence on the heat transfer process; B_w and H_w are water surface width and flow depth, respectively, and they represent the boundary conditions of the channel; P is the average daily pressure; Ra is the solar radiation; Rel is the average daily relative humidity; Rp is the average daily precipitation; E is average daily evaporation; and Hc is the cloud height.

Since Eq. (1) describes the physical law of the change of water temperature, it can be used as a constraint on the water temperature change. These factors have a more complex non-

linear impact on the change of the generalized heat exchange coefficient f_{wa} . Therefore, the neural network combined with the gradient descent method is used to calibrate the effect of the parameter f_{wa} under different environmental conditions, and then to form a model for simulating and predicting water temperature, as shown in Figure 5.

3 SIMULATION AND PREDICTION OF WATER TEMPERATURE

3.1 Analysis of influencing factors of water temperature

The simulation technology for the variation of water temperature covers the thermal-hydrodynamic and ice process of water body in the water transfer channel. It is essential to assess and identify the influencing factors and their effects on the water temperature in the transfer channel.

Data of field observations showed that the changes of water temperature in MR-StNWTP is highly correlated with the appearance of cold waves. At the typical observation cross section, the cumulative negative air temperature from 2015 to 2016 reached -310.14 °C, -92.53 °C from 2016 to 2017, and -193.92 °C from 2017 to 2018. These cumulative negative air temperature values characterized the situation during these three winters. For the part of the MR-StNWTP channel in northern China, negative cumulative air temperature is monotonically

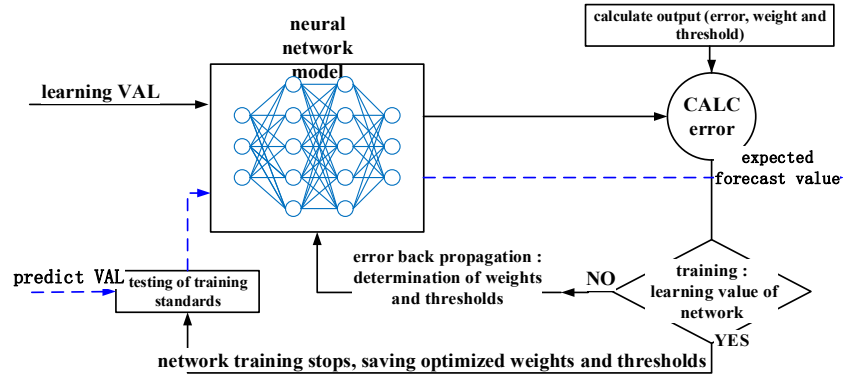


Fig. 4. Calculation flow chart of the neural network method.

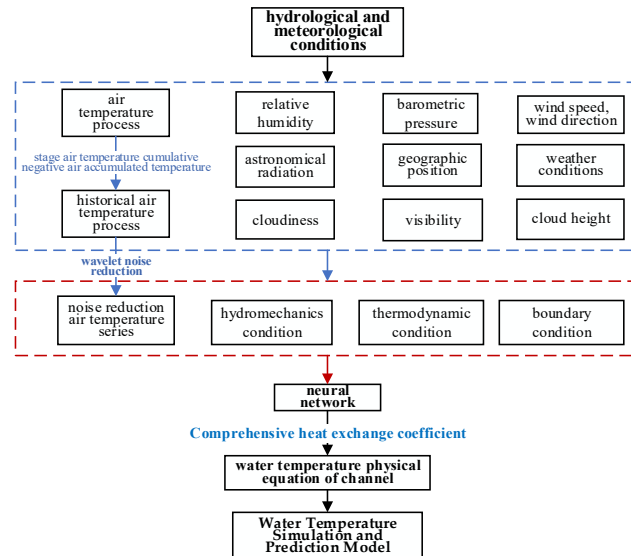


Fig. 5. Flow chart for simulation of water temperature using the wavelet noise reduction-deep-learning method.

increasing during a winter. However, there is lack of expression for describing the mechanism for the heating process after a winter cold wave. Results showed that the air-temperature will rise to above 0°C once the cold wave is over. To express the influence of the changes of air-temperature after a cold wave on the water temperature, it is necessary to consider the concept of the “cumulative air-temperature during a period” after the cold wave. Figure 6 shows the relationship between the “cumulative air-temperature for a period of 3 days” and water temperature during these 3 days.

Results of the correlation analysis among the influencing factors indicated that, there is a certain correlation between water temperature and the cumulative air-temperature during a period, implying that the variation of this factor has approximately similar trend to that of the daily average water temperature. The correlation between air temperature and water temperature is influenced by different meteorological, hydraulic, and thermal conditions. Using the cumulative negative air temperature and cumulative air-temperature during a period, the ice phenomenon in the channel and the variation of channel bed temperature (ground temperature) can be more effectively characterized. Since both the ice phenomenon in the channel and the channel bed temperature affect the change of water temperature, these two factors will be considered as important factors affecting water temperature.

3.2 Wavelet noise reduction and water temperature simulation

In practical engineering applications, noise signals (such as air temperature) are usually expressed as high-frequency signals. By means of the scale function which is almost everywhere differentiable, the air temperature process can be decomposed by the tower algorithm method by combining the Mallat binary wavelet transformation and multi-resolution. The noise reduction can be achieved through the reconstruction.

The effect of noise reduction depends on how to select the threshold function and how to quantify the threshold. The principle for the threshold selection based on sample estimation is to estimate the signal to determine the threshold. Then, the coefficients that exceed the threshold will be retained, and the coefficients that are less than the threshold will be cut off. Through such an approach, a threshold noise reduction will be formed. The threshold de-noising method is applied to denoise the data of the average air temperature, and the results are shown in Figure 7.

It can be seen from Figure 7 that after noise reduction of the daily air temperature data, the variation of air temperature has certain similarity to that of water temperature but retains certain details. The noise reduction process based on the wavelet decomposition possesses a good noise reduction effect on the daily

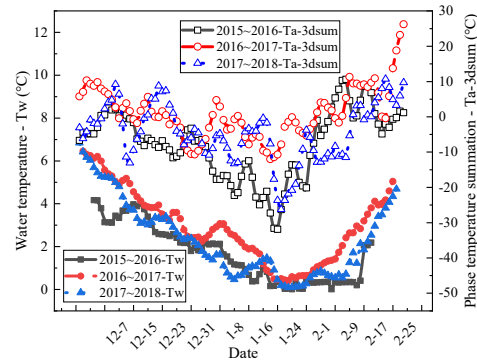


Fig. 6. Variation of water temperature and the cumulative air-temperature for a period of 3 days.

average air temperature process. In view of the nonlinear relationship between the air temperature and water temperature process in Eq. (1), the process of air temperature after noise reduction can be derived almost everywhere. The previous water temperature series, air temperature noise reduction series, radiation and evaporation series are brought into Eq. (1) respectively, and the water temperature process at the corresponding cross section can be obtained.

The above-proposed physical temperature equation combined with the neural network (TE-NN) method is used for simulation analysis. Both the neural network (NN) method and the multiple regression (MR) method are used for comparison. The water temperature at the typical cross section of the Beijuma River in the MR-StNWTP from 2018 to 2019 has been simulated. Whether or not the air temperature is subjected to the noise reduction (NR) to form a comparison, the simulation results of water temperature are obtained as shown in Figure 8. Results of both simulations and field observations are analyzed. Also, the corresponding maximum error (MaxAE), mean error (MeanAE), maximum relative error (MaxRE), mean relative error (MeanRE), correlation coefficient (R) and root mean square error (RMSE) are calculated. Results of the Mann-Kendall trend (M-K) and variance analysis (F-value, P-value) are shown in Table 1.

After treatment of wavelet decomposition and noise reduction, the temperature series is used as input data to train to simulate the water temperature, and achieve better simulation results of water temperature, as showed in Figure 8. This simulation method can better track the variation process of water temperature. Results indicate that, after wavelet decomposition and noise reduction, the data effect is good, and the mean absolute error and average relative error are less than those using the model without wavelet noise reduction, which is more obvious by using the neural network method.

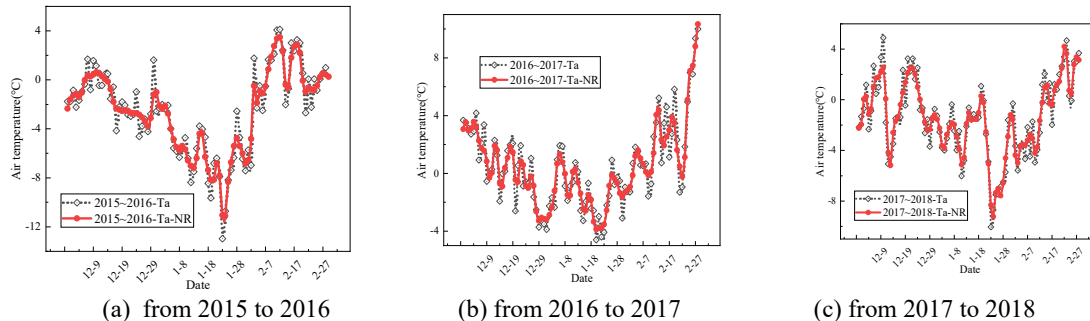


Fig. 7. Noise reduction of the average air temperature by wavelet decomposition.

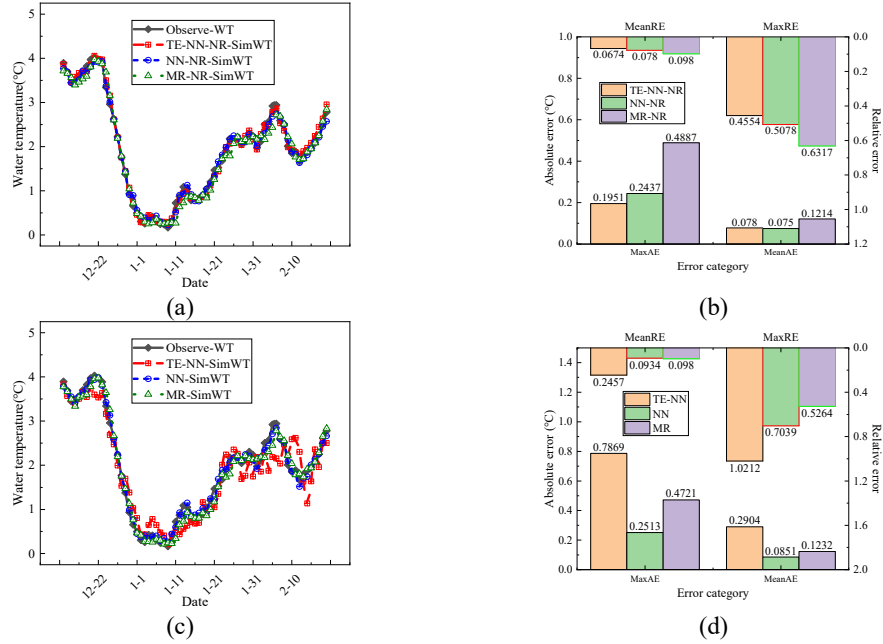


Fig. 8. Simulation analysis of daily mean water temperature: (a) wavelet noise reduction processing simulation; (b) wavelet noise reduction processing simulation error; (c) simulation without wavelet noise reduction; (d) simulation error without wavelet noise reduction.

Table 1. Error analysis of water temperature (TEMP) simulation using different methods.

Water TEMP simulation model	TE-NN-NR-SimWT	TE-NN-SimWT	NN-NR-SimWT	NN-SimWT	MR-NR-SimWT	MR-SimWT
MaxAE	0.1951	0.7869	0.2437	0.2513	0.4887	0.4721
MeanAE	0.0780	0.2904	0.0750	0.0851	0.1214	0.1232
MaxRE	0.4554	1.0212	0.5078	0.7039	0.6317	0.5264
MeanRE	0.0674	0.2457	0.0780	0.0934	0.0980	0.0980
R	0.9965	0.9537	0.9966	0.9960	0.9899	0.9900
RMSE	0.0951	0.3469	0.0960	0.1029	0.1659	0.1627
M-K trend	79.9948	-15.9948	7.9948	47.9948	73.9948	79.9948
F - Test value	0.9522	0.5148	0.8257	0.8325	0.9977	0.9897
P - Test value	0.9519	0.6786	0.9626	0.9812	0.8119	0.8423

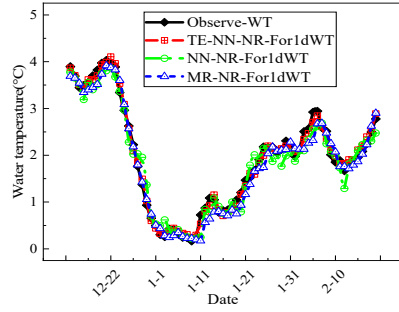
Results of error analysis (Table 1) showed that the simulation results of water temperature process using both the neural network and multiple regression methods are also fair. When the accuracy requirements are relatively low, these two methods can be used instead of solving physical equations. However, due to the lack of the mechanism of variation of water temperature which is an important control factor, the directly applications of either neural network method or multiple regression method will cause a further increase in the forecast error in the later period of the winter. Due to the constraints for theoretically solving Eq. (1), the wavelet noise reduction model using the physical equation combined with the neural network method is obviously superior to other models, which will be particularly important when the corresponding method is used to predict the water temperature later. The M-K trend value of the observed water temperature sequence is 21.995. If the wavelet method is not used to reduce the noise of the air temperature, the simulation based on physical equation combined with the neural network method will produce the corresponding deviation.

3.3 Prediction and analysis of water temperature

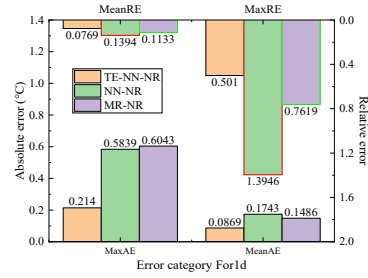
In terms of prediction of water temperature, the observation data during winter periods from 2015 to 2018 are selected as

training samples, and the data from 2018 to 2019 are selected as test samples. Since the annual cumulative negative air temperature of the training samples covers a certain range of variation, the training samples should represent different winter characteristics, and it is appropriate to use them as a training set. The changes in air temperature were more dramatic during the winter period of 2018–2019, but the lowest water temperatures appeared earlier than the previous years. These differences present a challenge to water temperature prediction, and illustrate the value of the new approach that can be demonstrated using the period of 2018–2019 as a prediction set. In view of the predictability of meteorological data, the meteorological data series and the previous water temperature series are used as input variables, and the predicted water temperature series is used as output variables. In the preprocessing part of the “input-output” matrix, the air temperature sample matrix is decomposed and denoised by means of the wavelet analysis method. The method is consistent with the method used in Section 3.2, and the water temperature at the observation cross section is then predicted for the next couple of days (1, 3, 5, 7 days). The prediction results are shown in Figure 9.

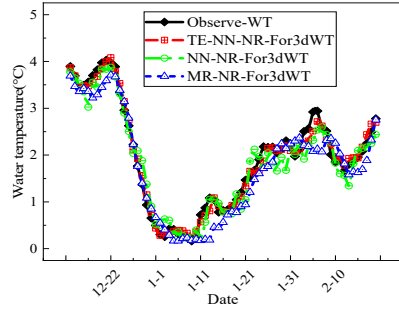
It can be seen from Figure 9 that the predicted water temperature by using the air temperature series after treatment through the wavelet decomposition and noise reduction as the input data



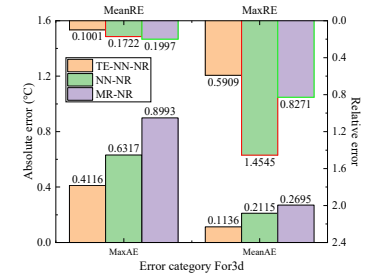
(a)



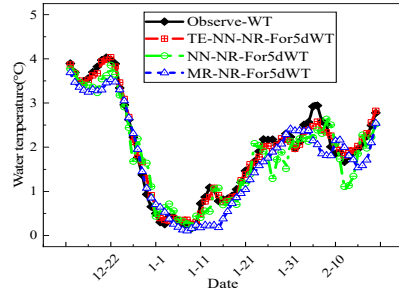
(b)



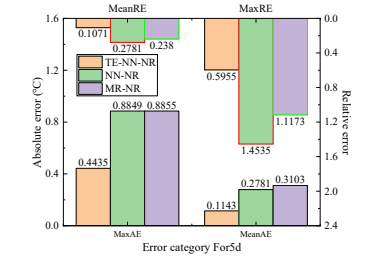
(c)



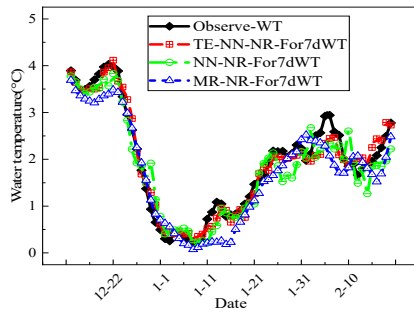
(d)



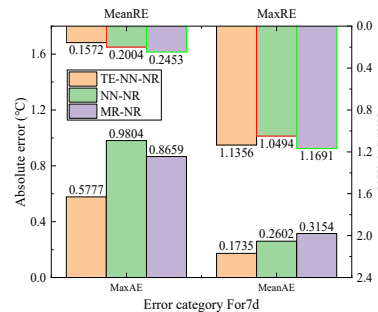
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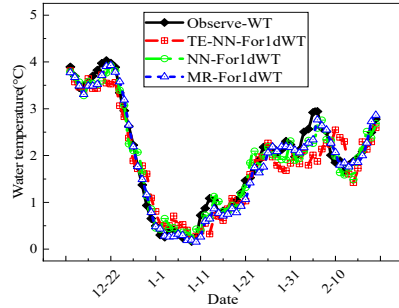
(f)



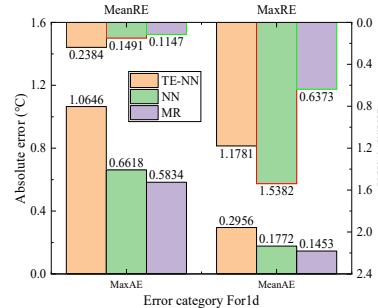
(g)



(h)



(i)



(j)

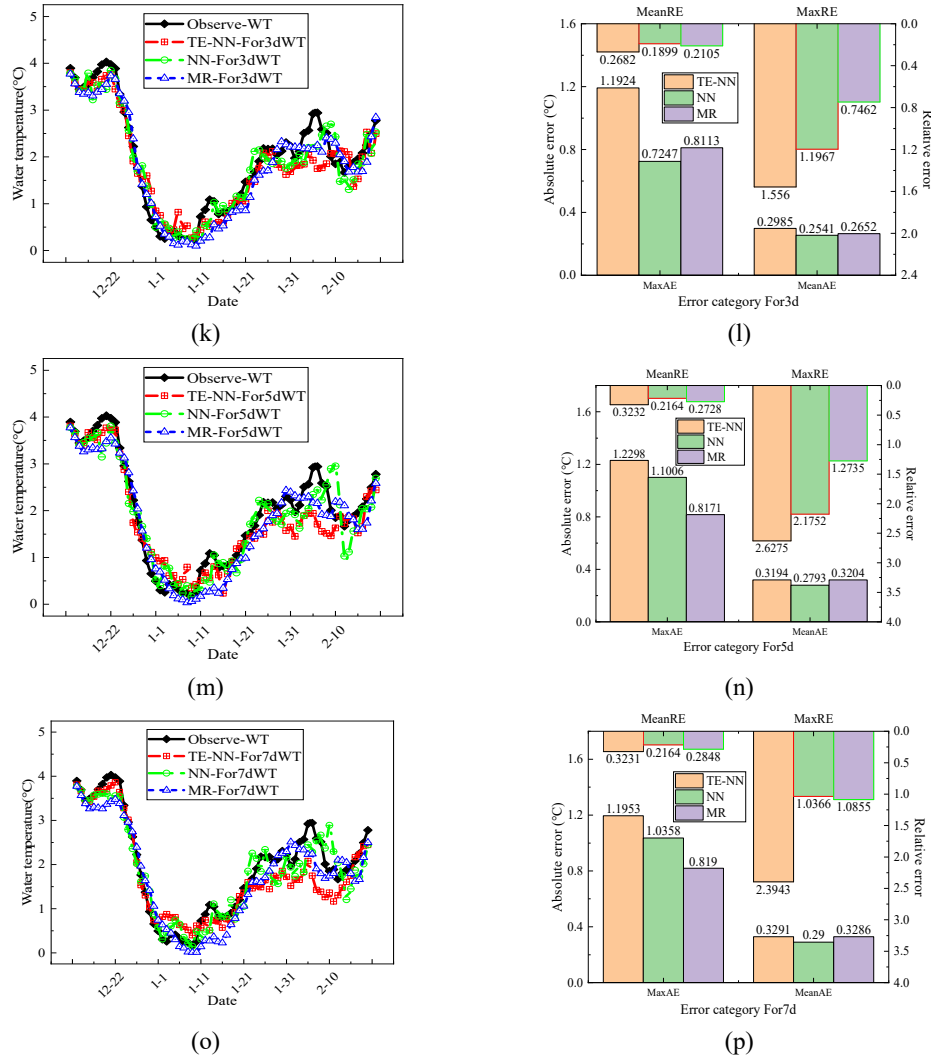


Fig. 9. Prediction of water temperature at the Beijuma-River CS using wavelet noise reduction: (a) wavelet noise reduction processing prediction (1d); (b) wavelet noise reduction processing prediction error (1d); (c) wavelet noise reduction processing prediction (3d); (d) wavelet noise reduction processing prediction error (3d); (e) wavelet noise reduction processing prediction (5d); (f) wavelet noise reduction processing prediction error (5d); (g) wavelet noise reduction processing prediction (7d); (h) wavelet noise reduction processing prediction error (7d); (i) prediction without wavelet noise reduction (1d); (j) prediction error without wavelet noise reduction (1d); (k) prediction without wavelet noise reduction (3d); (l) prediction error without wavelet noise reduction (3d); (m) prediction without wavelet noise reduction (5d); (n) prediction error without wavelet noise reduction (5d); (o) prediction without wavelet noise reduction (7d); (p) prediction error without wavelet noise reduction (7d).

training obviously has a high accuracy than that using the original air temperature series without a treatment. By means of this approach, the variation process of water temperature can be more precisely predicted. Also, the prediction errors are analyzed, as shown in Table 2.

Results showed that the correlation coefficient by using all models can reach 0.90 or more, indicating that the predicted values using these models agree well with water temperature measured in the field. After the air temperature series are processed by means of the wavelet noise reduction, the mean absolute error and mean relative error of the predicted values are decreased, which indicates that the wavelet noise reduction is beneficial for improving the prediction accuracy of the model. With the increase in the length of forecasting period, mean error (MeanAE), mean relative error (MeanRE), root mean square error (RMSE) and other error terms show an increasing trend. This means that as the length of the forecasting period increases, the difference

between the predicted value and the real value will increase, indicating that the wavelet noise reduction method will play a role in controlling the error diffusion. From the perspective of trend analysis, the physical temperature model based on the neural network method combined with the wavelet noise reduction has a more consistent trend of prediction. With the increase in the length of the prediction period, the trend error of predictions by using other methods gradually increases. Results of variance analysis show that the dispersion of residual distribution will increase with the increase in the length of the prediction period.

According to the field observations, the critical condition for ice regime at the typical observation cross section is closely related to the water temperature. When the average water temperature drops below 2.5 °C, the ice formation process is obviously observed. At this stage, more accurately forecast of water temperature during a winter period is required. The physical model for water temperature is combined with the neural network

Table 2a. Error analysis of predicted water temperature (TEMP) at the Beijuma-River CS by using the TE-NN method.

Water TEMP model prediction period	TE-NN-NR				TE-NN			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.2140	0.4116	0.4435	0.5777	1.0646	1.1924	1.2298	1.1953
MeanAE	0.0869	0.1136	0.1143	0.1735	0.2956	0.2985	0.3194	0.3291
MaxRE	0.5010	0.5909	0.5955	1.1356	1.1781	1.5560	2.6275	2.3943
MeanRE	0.0769	0.1001	0.1071	0.1572	0.2384	0.2682	0.3232	0.3231
R	0.9961	0.9923	0.9918	0.9813	0.9509	0.9498	0.9433	0.9412
RMSE	0.0996	0.1396	0.1448	0.2169	0.3663	0.3804	0.4162	0.4332
M-K trend	91.9948	101.9948	77.9948	97.9948	-5.9948	-5.9948	-49.9948	-111.9948
F - Test value	0.9844	0.8903	0.8294	0.7839	0.4330	0.4131	0.3676	0.4590
P - Test value	0.9983	0.9493	0.9667	0.9178	0.5515	0.4462	0.3251	0.2569

Table 2b. Error analysis of predicted water temperature (TEMP) at the Beijuma-River CS by using the NN method.

Water TEMP model prediction period	NN-NR				NN			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.5839	0.6317	0.8849	0.9804	0.6618	0.7247	1.1006	1.0358
MeanAE	0.1743	0.2115	0.2781	0.2602	0.1772	0.2541	0.2793	0.2900
MaxRE	1.3946	1.4545	1.4535	1.0494	1.5382	1.1967	2.1752	1.0366
MeanRE	0.1394	0.1722	0.2159	0.2004	0.1491	0.1899	0.2164	0.2164
R	0.9823	0.9737	0.9580	0.9599	0.9816	0.9625	0.9498	0.9518
RMSE	0.2232	0.2716	0.3462	0.3359	0.2228	0.3197	0.3663	0.3582
M-K trend	-23.9948	-73.9948	-53.9948	-97.9948	0.0000	-67.9948	-101.9948	-103.9948
F - Test value	0.6526	0.5813	0.5052	0.5560	0.6421	0.5903	0.5697	0.5353
P - Test value	0.7253	0.6577	0.5061	0.5338	0.7963	0.6073	0.5678	0.5940

Table 2c. Error analysis of predicted water temperature (TEMP) at the Beijuma-River CS by using the MR method.

Water TEMP model prediction period	MR-NR				MR			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.6043	0.8993	0.8855	0.8659	0.5834	0.8113	0.8171	0.8190
MeanAE	0.1486	0.2695	0.3103	0.3154	0.1453	0.2652	0.3204	0.3286
MaxRE	0.7619	0.8271	1.1173	1.1691	0.6373	0.7462	1.2735	1.0855
MeanRE	0.1133	0.1997	0.2380	0.2453	0.1147	0.2105	0.2728	0.2848
R	0.9872	0.9669	0.9588	0.9578	0.9872	0.9672	0.9579	0.9552
RMSE	0.1973	0.3364	0.3825	0.3881	0.1921	0.3237	0.3739	0.3879
M-K trend	41.9948	-53.9948	-149.9948	-177.9948	57.9948	-63.9948	-151.9948	-175.9948
F - Test value	0.9927	0.8634	0.7442	0.7072	0.9844	0.9358	0.8311	0.7748
P - Test value	0.6629	0.3528	0.2604	0.2489	0.7212	0.4256	0.3171	0.2872

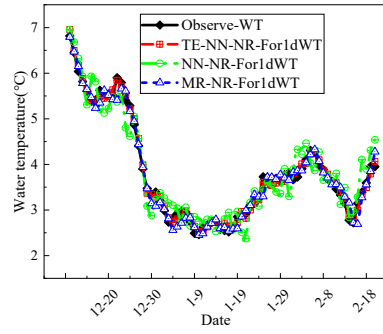
method considering the corresponding hydraulic parameters, time parameters, and integrates the air temperature parameters after noise reduction. The prediction accuracy of water temperature using the proposed approach has been improved compared to that using other models. By using the proposed approach, provided the average water temperature is below 2.5 °C, the forecasted date for ice formation agrees very well with that of the field observations, which is of great significance for the operation of water transfer channels during winter periods. For a prediction period of 7 days, the maximum error for the prediction of water temperature using the proposed method is less than 0.6 °C, and the error diffusion trend is small, implying a good prediction approach.

3.4 Application and generalization of the proposed approach

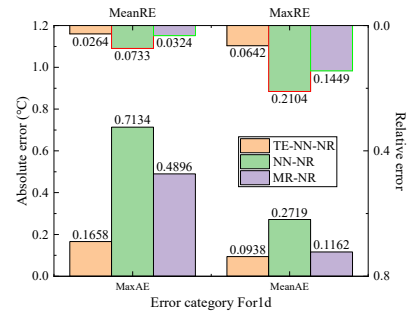
The cross section at the Hutuo-River sluice gate (abbreviated as the Hutuo-River-CS) of the MR-StNWTP is an upstream cross section of the Beijing-Shijiazhuang canal reach of the MR-StNWTP, as shown in Figure 1. Both the air temperature and water temperature are higher than those at the downstream Beijuma-River cross section (abbreviated as the Beijuma-River-CS). For the MR-StNWTP, in winter, the water is generally transported to the Hutuo River channel section. The water flow rate at the Hutuo-River-CS is about twice in the Beijuma-River-CS. In order to avoid the influence of training samples on the

generalization ability of the model, the water temperature dataset at the Hutuo-River-CS is selected for prediction analysis to test the practicability of the proposed approach. The prediction results are shown in Figure 10, and the results of analysis of prediction errors are shown in Table 3.

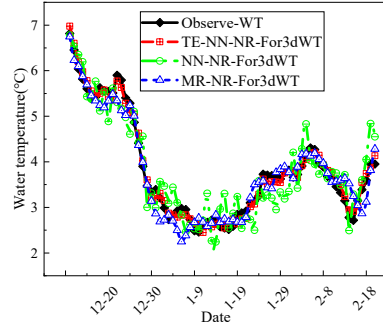
The results of prediction of water temperature at the Hutuo-River-CS agree well with those of field measurements. Similar to the results of prediction of the water temperature at the Beijuma-River-CS, after the air temperature series have been processed by means of the wavelet noise reduction, the mean absolute error and mean relative error of the predicted values are decreased, indicating that the wavelet noise reduction is beneficial for improving the prediction accuracy of the model. With the increase in the length of forecasting period, mean error (MeanAE), mean relative error (MeanRE), root mean square error (RMSE) and other error terms show an increasing trend. This means that as the length of the forecasting period increases, the difference between the predicted values and the real values will increase, indicating that the wavelet noise reduction method will play a role in controlling the error diffusion. Results of analysis showed that the generalization ability of the proposed approach is good. The deep learning based on physical model can overcome the limitations of multiple regression and neural network methods to a certain extent, and is more robust in the application for predicting water temperature along a channel during winter periods.



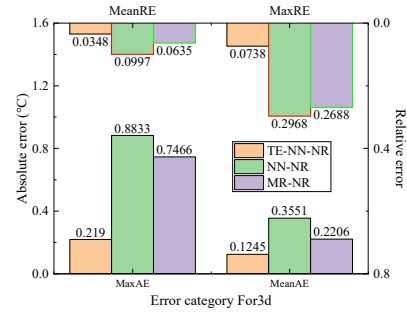
(a)



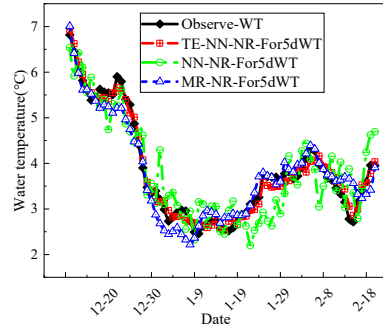
(b)



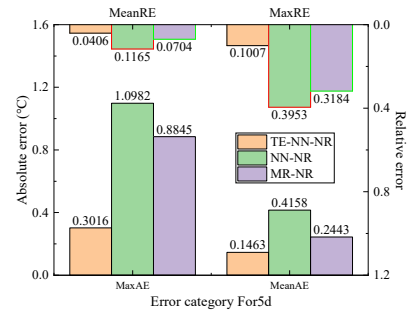
(c)



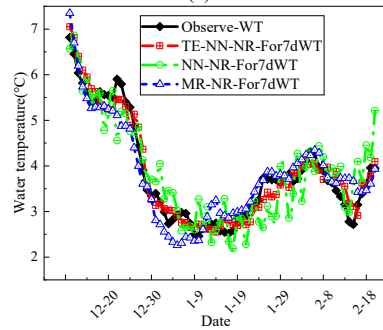
(d)



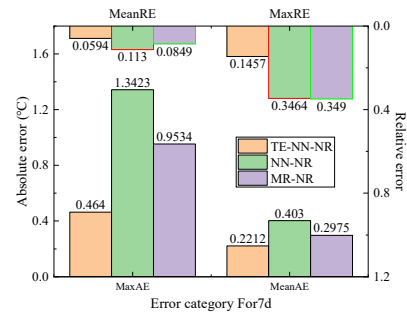
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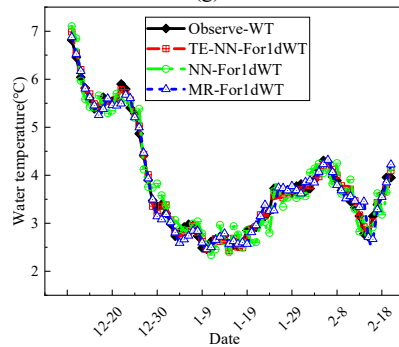
(f)



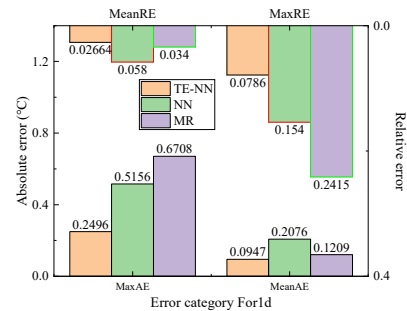
(g)



(h)



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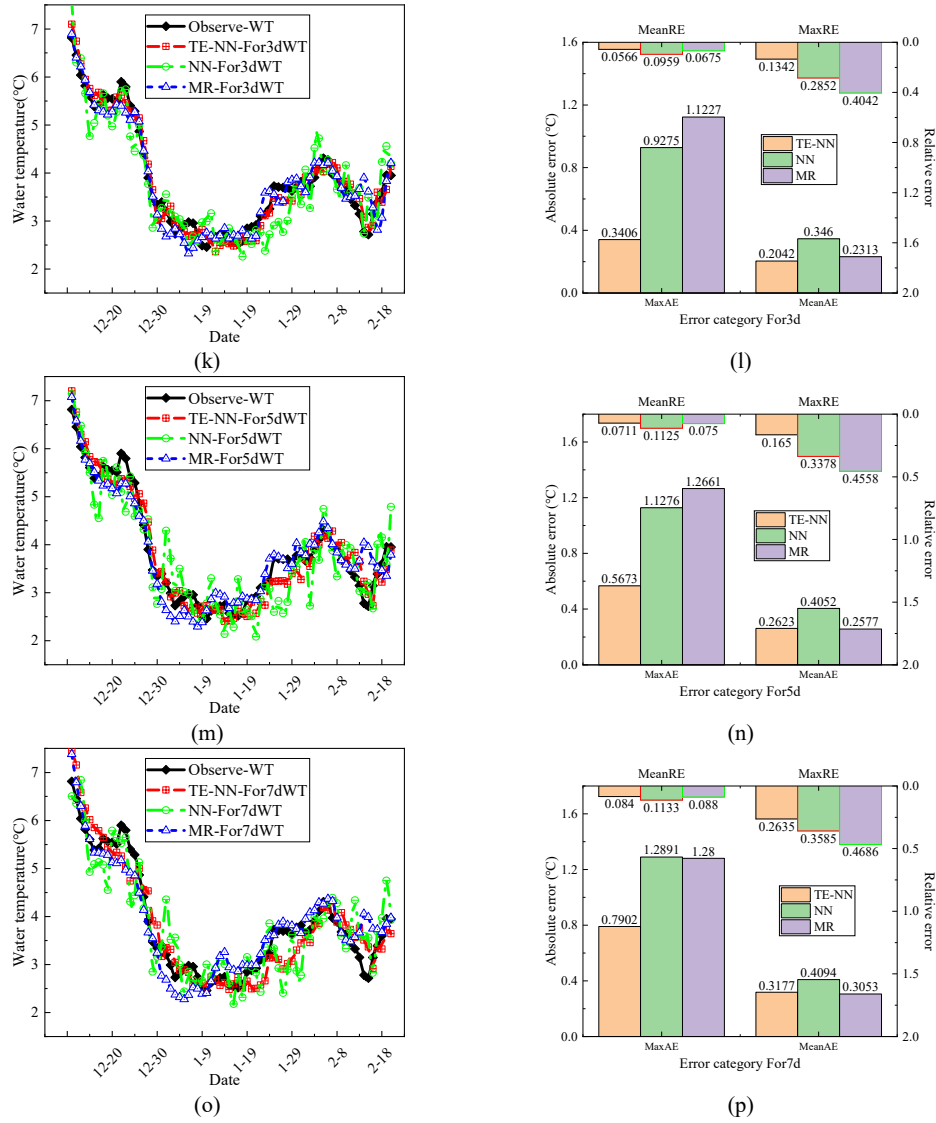


Fig. 10. Prediction of water temperature at the Hutuo-River-CS using wavelet noise reduction: (a) wavelet noise reduction processing prediction (1d); (b) wavelet noise reduction processing prediction error (1d); (c) wavelet noise reduction processing prediction (3d); (d) wavelet noise reduction processing prediction error (3d); (e) wavelet noise reduction processing prediction (5d); (f) wavelet noise reduction processing prediction error (5d); (g) wavelet noise reduction processing prediction (7d); (h) wavelet noise reduction processing prediction error (7d); (i) prediction without wavelet noise reduction (1d); (j) prediction error without wavelet noise reduction (1d); (k) prediction without wavelet noise reduction (3d); (l) prediction error without wavelet noise reduction (3d); (m) prediction without wavelet noise reduction (5d); (n) prediction error without wavelet noise reduction (5d); (o) prediction without wavelet noise reduction (7d); (p) prediction error without wavelet noise reduction (7d).

Table 3a. Error analysis of predicted water temperature (TEMP) the the Hutuo-River-CS by using the TE-NN method.

Water TEMP model prediction period	TE-NN-NR				TE-NN			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.1658	0.2190	0.3016	0.4640	0.2496	0.3406	0.5673	0.7902
MeanAE	0.0938	0.1245	0.1463	0.2212	0.0947	0.2042	0.2623	0.3177
MaxRE	0.0642	0.0738	0.1007	0.1457	0.0786	0.1342	0.1650	0.2635
MeanRE	0.0264	0.0348	0.0406	0.0594	0.0266	0.0566	0.0711	0.0840
R	0.9957	0.9928	0.9891	0.9746	0.9954	0.9813	0.9663	0.9484
RMSE	0.1039	0.1358	0.1654	0.2546	0.1105	0.2247	0.3038	0.3850
M-K trend	-495.9951	-515.9951	-509.9951	-497.9951	-479.9951	-555.9951	-605.9951	-659.9951
F - Test value	0.9761	0.9289	0.9886	0.9170	0.8834	0.7526	0.6919	0.5262
P - Test value	0.9983	0.9493	0.9667	0.9178	0.9817	0.9751	0.8788	0.8758

Table 3b. Results of error analysis of predicted-water temperature (TEMP) at the Hutuo-River-CS by using the NN method.

Water TEMP model prediction period	NN-NR				NN			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.7134	0.8833	1.0982	1.3423	0.5156	0.9275	1.1276	1.2891
MeanAE	0.2719	0.3551	0.4158	0.4030	0.2076	0.3460	0.4052	0.4094
MaxRE	0.2104	0.2968	0.3953	0.3464	0.1540	0.2852	0.3378	0.3585
MeanRE	0.0733	0.0997	0.1165	0.1130	0.0580	0.0959	0.1125	0.1133
R	0.9590	0.9300	0.8980	0.8951	0.9769	0.9317	0.9022	0.8908
RMSE	0.3190	0.4183	0.5013	0.5101	0.2423	0.4245	0.5104	0.5173
M-K trend	-495.9951	-541.9951	-693.9951	-577.9951	-661.9951	-509.9951	-619.9951	-513.9951
F - Test value	0.8722	0.9734	0.8498	0.9009	0.9229	0.8727	0.7993	0.7884
P - Test value	0.9016	0.9962	0.8952	0.8805	0.9863	0.7050	0.6734	0.8598

Table 3c. Results of error analysis of predicted water temperature (TEMP) at the Hutuo-River-CS by using the MR method.

Water TEMP model prediction period	MR-NR				MR			
	1d	3d	5d	7d	1d	3d	5d	7d
MaxAE	0.4896	0.7466	0.8845	0.9534	0.6708	1.1227	1.2661	1.2800
MeanAE	0.1162	0.2206	0.2443	0.2975	0.1209	0.2313	0.2577	0.3053
MaxRE	0.1449	0.2688	0.3184	0.3490	0.2415	0.4042	0.4558	0.4686
MeanRE	0.0324	0.0635	0.0704	0.0849	0.0340	0.0675	0.0750	0.0880
R	0.9898	0.9678	0.9586	0.9431	0.9883	0.9610	0.9492	0.9359
RMSE	0.1620	0.2856	0.3216	0.3726	0.1727	0.3113	0.3527	0.3969
M-K trend	-511.9951	-417.9951	-415.9951	-307.9951	-507.9951	-417.9951	-379.9951	-217.9951
F - Test value	0.9974	0.7977	0.6478	0.6998	0.9736	0.8899	0.7569	0.7896
P - Test value	0.8879	0.8050	0.8326	0.9588	0.9289	0.9042	0.9618	0.9064

4 CONCLUSIONS AND DISCUSSION

In this study, the air-water heat exchange coefficient h_{wa} in equations for describing water temperature is taken as the breakthrough point, considering its response to the changes of air temperature, solar radiation, cloud layer, wind speed and other factors. The mechanisms of water temperature change at the typical cross section of the MR-StNWTP under the combined interaction of thermodynamic, hydrodynamic, ice regime and channel boundary conditions are considered. The air temperature data have been preprocessed by means of the wavelet decomposition noise reduction, and the variation of water temperature at the typical cross section has been simulated and predicted. The main conclusions have been drawn as follows:

1) The decrease in air temperature in winter is normally accompanied by several cold waves with different intensities. On the other side, the air temperature will rise after the cold wave in warm winter, which has an important impact on water temperature. However, the change of air temperature series is more intense than that of water temperature. Through the comparative analysis, it has been found that the wavelet noise reduction method can be applied to process the air temperature series simply and efficiently, which is more suitable for the study of water temperature.

2) Considering the complex regional meteorological conditions in winter along the MR-StNWTP channel, the Beijuma River section is selected as a typical cross section for field observations. By identifying the mutual feedback relationship between each meteorological correlation parameter and water temperature, to replace the traditional linear relationship between air temperature and water temperature, the physical equation for describing water temperature is combined with the nonlinear relationship between multiple meteorological factors such as air temperature, solar radiation, cloud layer, precipitation and wind speed. The variation of water temperature at the typical cross section during winter periods has been simulated. Simulation results of water temperature are in good agreement with those of field observations.

3) By applying either the multiple regression or neural network method alone, due to the limitations of the method at the mechanism level, the errors in the simulation and prediction of water temperature are relatively larger, namely, it is difficult to achieve an accurate simulation and prediction. The air-water temperature process needs to be further identified. The proposed approach for simulation and prediction of water temperature combines both physical equation for describing the mechanism of water temperature change and the advantages of the neural network method in nonlinear mapping. Consequently, it can provide essential technical support for the simulation and prediction of ice conditions in the channel.

There is a difference in specific heat between water and air, and this difference has affected the prediction accuracy using previous reported methods. To overcome this challenge, a new model is proposed that integrates neural network theory into equations describing water temperature. The wavelet denoising method is applied to eliminate fluctuations in certain temperature data, followed by calculating the corresponding water temperature. In such a way, the new proposed method improves the accuracy of water temperature prediction. It is worth discussing that the sample data size has an impact on the calibration of parameters. This means that the limited measurement data which are available currently may lead the application of the proposed model to be inaccurate under extreme weather conditions. However, since the model is constrained in the physical theory, it is believed that the proposed model can accurately predict water temperature provided that the influencing factors and their threshold intervals are adequately analyzed. Existing empirical analysis shows that different water temperatures produce different types of ice, so an accurate prediction of water temperature in winter can better predict the ice situation, which is not only the innovative results of this study but also the future research direction. As a new time-frequency analysis tool, wavelet analysis has strong ability in analysis of signal detection and noise reduction. It also has broad application prospects. Introducing the wavelet analysis into the study of water temperature can provide reference for the early warning of

ice disaster in rivers. This will benefit the river ice control and related river engineering projects.

Statements and Declarations

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Competing Interests. The authors have no relevant financial or non-financial interests to disclose.

Author Contributions. All authors contributed to the study conception and design, data collection, material preparation. The first draft of the manuscript was written by [Tiejie Cheng] and [Jueyi Sui] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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