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Multi input–single output models identification of tower bridge movements using GPS monitoring system

Mosbeh R. Kaloop [a,*], Hui Li [b]

[a] Public Works and Civil Engineering Department, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt
[b] School of Civil Engineering, Harbin Institute of Technology, Harbin 150090, China

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ABSTRACT

In this paper, RTK-GPS system was used for movement data collection. Two identification models namely; Multi input–single output (MISO) robust fit regression and Neural Network Auto-Regression Moving Average with eXogenous input (NNARMAX) models were used for the identification of these data. The analysis of test results indicate that: (1) the NNARMAX [4 4 1 1] and [5 4 1 5] models defined by taking into account the results of robust regression analysis estimate structural movements more accurately than the NNARMAX [0 1 0 0] model, and (2) the robust fit regression models have good capacities for mapping relationship of applied loads effects factors and displacements of tower. However, temperature and humidity effects on the entire modal shapes are insignificant and (3) the traffic loads are the main factor affects tower bridge displacement.

1. Introduction

Global Positioning System (GPS) monitoring has been interested in a sensing technology of the structural responses to monitor the condition of a structure because basic data are obtained by field measurements. Also, GPS can be used in the displacement monitoring of large structures directly, whereas the GPS can be measured the three dimensional coordinates of the monitoring points [1,2].

Bridges are one of the important infrastructures in the national economy, which are considered the crucial links in transport network. Many bridge failures caused by normal or abnormal loadings. Monitoring the bridge deformation is the vital task in bridge maintenance and management. The process of implementing a damage identification strategy for aerospace, civil and mechanical engineering infrastructure is referred to as structural health monitoring (SHM).

Dynamic measurements of several high-rise building, suspension bridges and offshore structures were undertaken and used in system identification [3,4]. During this period the interest in using parametric time domain models for system identification of structural systems increased. In civil engineering, the use of multivariate time domain models has especially attracted the attention, see [5,6–11].

The system models can be simulating the effects of the physical laws pertaining to the system when available with the help of input–output quantities [12,13]. In addition, when there is little information on the physical laws pertaining to the system or when the system is too complex, identification methods such as parametric identification are used to define the model of the system. In this case, preliminary assumptions are made on the order of complexity, input and output parameters of the system. The model is then expressed as the relationship between the selected system inputs and outputs [10,14,15].

However, the focus of this research is: (1) To examine the RTK-GPS technique in deformation monitoring of the bridge tower. (2) To develop parametric models to assess

* Corresponding author. Tel.: +20 050 2244403; fax: +20 050 2244690.
E-mail address: mosbeh.kaloop@gmail.com (M.R. Kaloop).

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the dynamic behavior of the Yonghe tower bridge utilizing RTK-GPS measurements. (3) To transfer functions express the relationship between the displacements of the southern tower in two directions (*X* and *Y*) and the variations of temperature, humidity, wind speed and number of vehicles on the bridge have been defined with the use of parametric MISO NNARMAX and robust fit regression models. (4) To find out the reasons affect tower bridge displacements.

2. Bridge description, GPS information and data collection

The Yonghe bridge links the two cities in China (Tianjin and Hangu). This bridge was constructed by pre-stressed concrete in December, 1987, closed in October 2006 because of cracks over mid-span and opened in August 2007 after rehabilitation. The Yonghe bridge has four lanes with the total length of 510.00 m, and main span of the bridge is 260.00 m (Fig. 1). For safety assurance, a sophisticated long-term SHM system has been designed and implemented by the Research Center of Structural Health Monitoring and Control of Harbin Institute of Technology (HIT) to monitor loads and response of the bridge. The SHM system for the Yonghe bridge comprises a data acquisition and processing system with a total of approximate 179 sensors, including accelerometers, strain gauges, displacement transducers, anemometers, temperature sensors, weight-in-motion sensors and three GPS's (Figs. 1 and 2b). The GPS's were permanently installed on the two towers tops of the bridge and bank near the bridge. The GPS observations are real time kinematic (RTK) with differential GPS (DGPS) system. The receivers are LEICA GMX902 antenna (24 channel L1/L2 code and phase, 20 HZ data rate, SmartTrack technology for high precession, accuracy of 1 mm + 0.5 ppm (horz.); 2 mm + 1 ppm (ver.)) and pre-processed data using the software GPS Spider 2.1. The coordinate components for each observation epoch are derived. Hence, the time sequences of positions for each station located on the bridge were generated. Two-rover observation stations were considered along the bridge in two tower of bridge, every rover station is observed for 24 h.

A local Bridge Coordinate System (BCS) was chosen for the analysis and evaluation procedures of the observations performed [11,18]. In this coordinate system, the *Y*-axis shows the traffic direction (span direction), the *X*-axis shows the lateral direction and the *Z*-axis gives the vertical direction of the bridge (Fig. 2a). It was assumed that this coordinate system would be beneficial for the evaluation of performed observations, description of the movement of the structure and allow a better interpretation of the analysis results as it is related to the movement directions of the structure.

3. Methods

3.1. GPS data pr-processing

During the complex noises in the GPS data, so to analyzing and identified the signals, a pre-processing should be done first [16,17]. That is to delete noises and extract useful signals. Wavelet analysis is a strong tool to eliminate noises according to the noise characteristics. There are two methods of eliminating noises. First one is a compulsive that the high frequency coefficients are processed to be zero in the decomposed signal constructions of wavelet analysis, and some scale or different scale signal components with these coefficients in the data time series are all eliminated. Then, the signals are reconstructed to analyze their spectrum features. Another method is a threshold eliminating noise processing that a threshold value is defined depending on experience, and used to process the high frequency coefficients of wavelet analysis, i.e. the coefficients greater than the threshold are reserved, and the coefficients less than it are processed to be zero [16]. In this research used de-noising process of a one-dimensional signal, which depended on the wavelet analysis. In this process used Daubechies40 wavelet at level 16 to decompose the original signal, then can obtain approximation coefficient (low frequency parts of original signal) and detail coefficients (high frequency parts of original signal), after that, reconstruct the signal using the approximation coefficient. For comparing the results after wavelet analysis with that of the former processing method without wavelet eliminating noises are present. This processing was implemented in MATLAB [19]. After that, the best straight-line fit is removed from the data before identification. This treatment enables the removal of the DC-components that can badly influence the identification results [17].

3.2. Identification models

In most practical applications the system is not known and has to be estimated from the available information. This is called the identification problem. The identification method will depend on the intended model use. The three

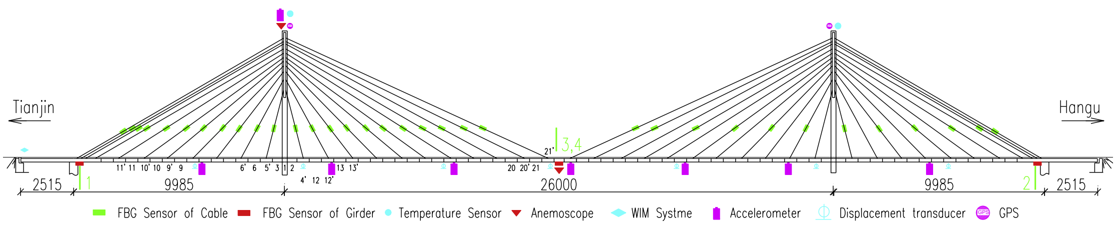

Fig. 1. Elevation and SHM system of Yonghe bridge.

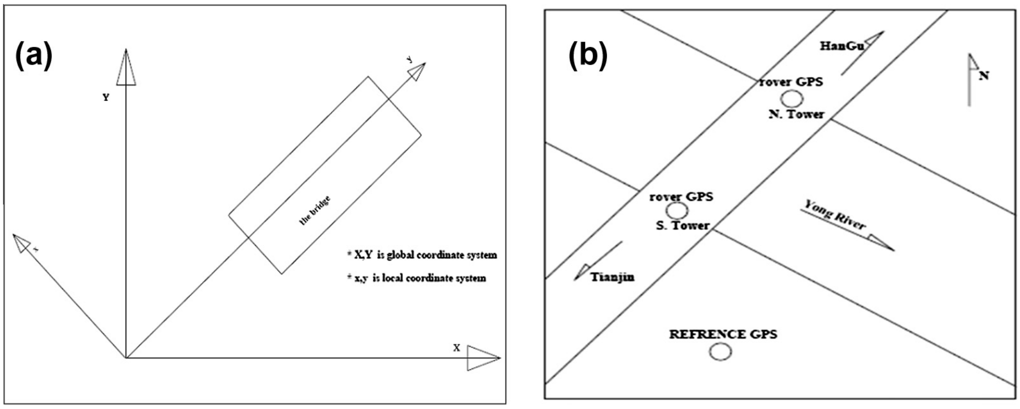

Fig. 2. The (a) global and local coordinate system and (b) layout of GPS positions of the Yonghe bridge.

main choices in system identification are data, modal class and criterion. In addition, system identification often involves several runs of the empirical cycle which consists of the specification of the problem, the estimation of a model by optimization of the criterion, the validation of the resulting model, and possible adjustments that may follow from this validation. However, in this section created two models identification between the multi-input data, temperature, wind, traffic, and humidity and single-output movement of tower in X and Y-directions. Using robust fitted regression and NNARMAX models as follow:

3.2.1. Robust fitted regression

The most common general method of robust regression is, introduced by [1]. Consider the fitted model:

$$y = a + b_1x_{i1} + b_2x_{i2} + \ldots\ldots + b_kx_{ik} + e_i \quad (i = 1, 2, \ldots\ldots, n) \tag{1}$$

Where y_i are the observed output quantities or signals, x_{i1}, x_{i2}, ... x_{ik} are the observed input quantities or signals, a, b_1, b_2, ... b_k are unknown parameters, the number of unknowns $u = k + 1$, k is the number of input quantities, n is the number of observations and e_i is the random error with $E(e_i) = 0$; $\mathrm{var}(e_i) = \sigma^2$. The unknowns form a vector of unknowns, U, i.e. $U^T = [a, b1, \ldots\ldots, bk]^T$. Unknown parameters X in Eq. (2) can be estimated and tested for statistical significance using the least squares method. The estimation process should be repeated after removing the insignificant parameters from the model (1).

$$U = (A^TPA)^{-1}A^TPy \tag{2}$$

$$V = y - AU \tag{3}$$

Where A is the design matrix, y is the vector of the n observed output quantities, V is the vector of the n residuals ($V^T = [v_1, \ldots\ldots, v_n]^T$) and P is the weight matrix ($P = \mathrm{diag}(w_1, \ldots\ldots, w_n)$), w_i is the chosen weight function in Eq. (4).

It is usually assumed that the response errors follow a normal distribution, and that extreme values are rare. Still, extreme values called outliers do occur. The main disadvantage of Least Square (LS) fitting is its sensitivity to outliers. Outliers have a large influence on the fit because squaring the residuals magnifies the effects of these extreme observation points. Bi-square weighted robust predictors were used in the regression analysis to minimize the influence of outliers. Bi-square weights; minimize a weighted sum of squares, where the weight given to each observation point depends on how far the point is from the fitted line. Points near the line get full weight. Points farther from the line get a reduced weight. Robust fitting with bi-square weights uses an iteratively re weighted LS algorithm, and follow the weight function.

$$w_i = \begin{cases} \left[1 - \left(\frac{v_i}{r}\right)^2\right]^2 & \text{for} |v_i| \leqslant r \\ 0 & \text{for} |v_i| > r \end{cases} \quad (r = 4.685) \tag{4}$$

Solving the robust model (1) is a weighted least-squares problem, minimizing $\sum w_i^2 v_i^2$. The weights, however, depend upon the residuals; the residuals depend upon the estimated coefficients, and the estimated coefficients depend upon the weights. An iterative solution is therefore required:

1. Select initial estimates U, such as the LS estimates. 2. At each iteration t, calculate residuals $e_i(t-1)$ and associated weights from Eq. (4) from the previous iteration. 3. Solve for new weighted-least-squares estimates using Eqs. (1) and (4). The procedure is completed when the fit converges. Otherwise, next iteration of the fitting procedure should be performed by returning to the first step [19].

3.2.2. The NNARMAX model

The general input–output model structure (Fig. 3) used for modeling of nonlinear and time invariant dynamic

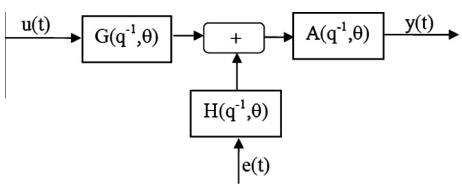

Fig. 3. ARMAX model structure.

systems excited by deterministic input is Auto-Regressive Moving Average with eXternal input (ARMAX), assuming unit sampling interval, there are an input and output quantity or signals $u(t)$ and $y(t)$ respectively, $t = 1, 2, \ldots\ldots n$. the input–output relationship can be written as [21]:

$$A(q^{-1},\theta)y(t) = G(q^{-1},\theta)u(t) + H(q^{-1},\theta)e(t) \tag{5}$$

where $A(q, \theta)$, $G(q, \theta)$, $H(q, \theta)$, θ are the parameter vector, $y(t)$ the output at time t ($t = 1, 2, \ldots\ldots$), $u(t)$ the input and $e(t)$ the stochastic input $e(t)$ are innovations, which is an equivalent process of the noise and prediction error.

To identify a neural network ARMAX (NNARAX) model, the nonlinear model is determines as follow:

$$\hat{y}(t|\theta) = g(y(t\ 1),\ldots\ldots,y(t\ n_a),u(t\ n_k),\ldots\ldots,u(t\ n_b\ n_k + 1),e(t\ 1),\ldots,e(t\ n_c)) \tag{6}$$

In the statements presented above, $\hat{y}(t|\theta)$ is the output neural network (prediction vector), n_a is the past output used for determining the prediction, n_b is the past input, n_k is the time delay, and n_c is the past residuals.

Herein, the Multilayer perceptron (MLP) network considered here is furthermore confidence to those having only one hidden layer and only hyperbolic tangent and linear activation function (f, F):

$$\hat{y}_i(w,W) = F_i\left(\sum_{j=0}^{q} W_{ij} f_j\left(\sum_{l=1}^{m} w_{jl} z_l + w_{j0}\right) + W_{i0}\right) \tag{7}$$

Here, w_{j0} and W_{i0} are the bias parameters; m is the number of input units; and q is the number of hidden units. The function $f(.)$ that is implemented in this paper is tangent function and $F(.)$ is linear function output. The weight (alternatively by the matrices w and W) are the adjustable parameters of the network, and they are determined from through the process called training. The training data are a set of input $u(t)$, and corresponding desired outputs $y(t)$. Specify the training set by [22]:

$$z_n = [u(t), y(t)] \quad t = 1, 2, \ldots\ldots, n \tag{8}$$

The objective of training is then to determine a mapping from the set of training data to the set of possible weights, so that the networks will predictions $\hat{y}(t)$, which are close to the true. The prediction error approach is based on the introduction of measure of closeness in terms of a mean of mean square error criterion [8,21]:

$$V_n(\theta, z_n) = \frac{1}{2n}\sum_{t=1}^{n} [y(t) - \hat{y}(t|\theta)]^T [y(t) - \hat{y}(t|\theta)] \tag{9}$$

The weights are then found:

$$\hat{\theta} = \arg\min\ V_n(\theta, z_n) \tag{10}$$

The NN model for ARMAX consists of three layers, i.e. one input layer (y, u, e), one hidden layers and one output layer $\hat{y}$. The identification method for the NNARMAX model is the Levenberg–Marquardt method, which provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the model. These minimization problems arise especially in least squares curve fitting and nonlinear programming. In addition, it does not only provide an estimate of the NNARMAX model parameters, but also, of the covariance matrix of the parameters. The square roots of the diagonal elements of this matrix are estimates of the standard deviations of individual model parameters. With this covariance matrix, it is also possible to estimate the standard deviations of a new observation. The standard deviations can be used to establish confidence intervals around the predicted values [8]. If a new observation lies outside the confidence intervals on the prediction, it is likely that the system is damaged [20].

The following criteria can be used to assess and compare the quality of models used. The first criterion: Model parameters have to be tested whether or not the deviations at the "0" expected values are significant. In order to do this, $\hat{t}$ test values can be calculated as follows: ($\hat{t}$ = parameter/parameter standard deviation); the testing values are compared with pre-determined $1-\alpha$ confidence levels and $t_{f,1-\alpha/2}$ confidence limit of t distribution dependent on the f order of freedom. As results of the test, insignificant parameters are excluded from the function and this procedure is continued till all parameters become significant [23,24].

The second criterion: is the value of the loss function, defined as:

$$\lambda_0 = \frac{1}{n}\sum_{t=1}^{n} e^2(t) \tag{11}$$

where $e(t)$ is a residual of the observation and the predicted model ($e(t) = y(t) - \hat{y}(t)$).

The third criterion includes penalties for model complexity similar to the Akaike's Final Prediction Error (FPE) criterion which is defined as:

$$\mathrm{FPE} = \lambda_0\left(1 + \frac{2k}{n-k}\right) \tag{12}$$

λ_0 is the loss function and k defines the number of parameters in the model. The FPE represents a balance between the number of parameters and the explained variation.

The fourth quality criterion for a model is provided by the Auto-Correlation Function (ACF) of the residuals. If the value of AC falls within 95% of the confidence interval, the AC value is insignificant and this value is considered to be equal to zero [21,22]. The final quality criterion for a prediction model is R-square; the R-square represents a balance between the old and the predicted data variation.

4. Results and discussions

4.1. Displacements of the tower

Three days continuous measurement of GPS, temperature, humidity, number of vehicle and wind velocity, which were from 0:00 of January 10, 2008 to 24:00 of January 12, 2008, are used in this study. The averages of all observations in the 20-min segment are plotted in Figs. 4 and 5. The original displacement history measurements in X and Y directions (BCS) on the tower were extracted using wavelet de-noising process. The trend components in the series were investigated from the

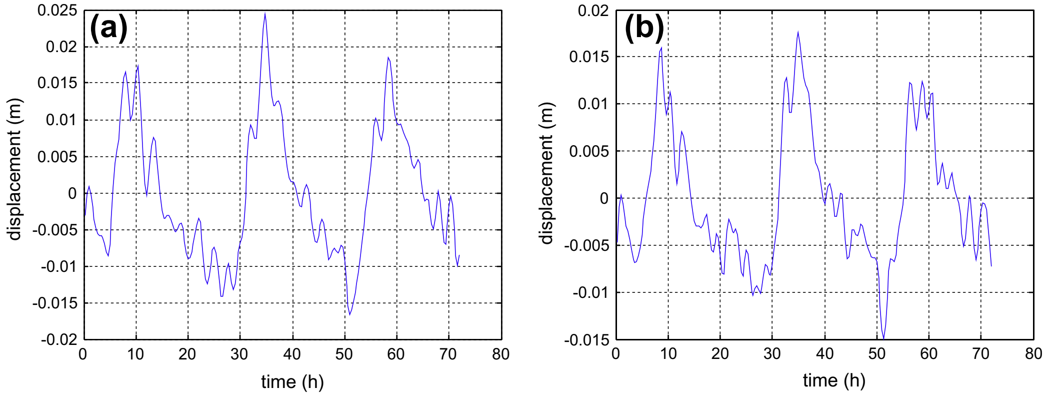

Fig. 4. Mean 20-min displacement of de-noised signals for southern tower in (a) *X* and (b) *Y*-directions.

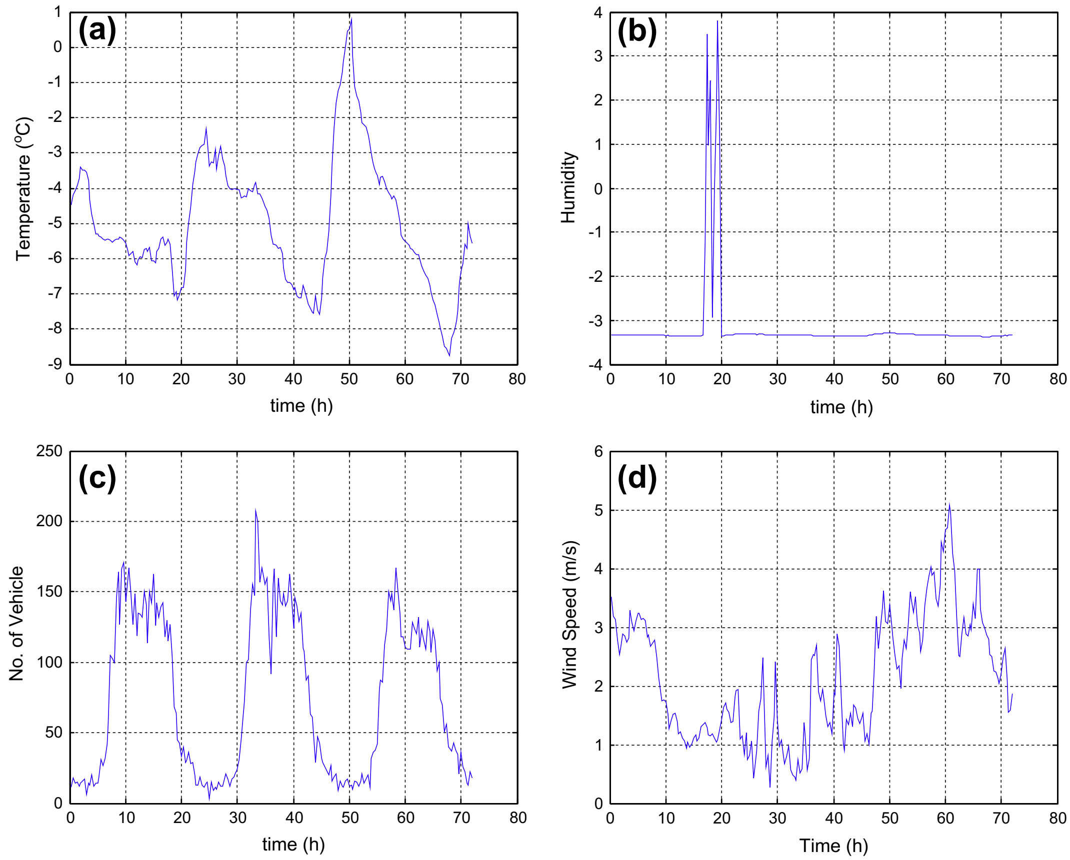

Fig. 5. Variation in (a) temperature, (b) humidity, (c) number of vehicle, and (d) wind speed during the observation.

obtained data within de-noising process analysis. The trend component in the series represents the long-term changes related to time and it can be defined by a polynomial function in the time domain. From Fig. 4, it was found that the de-noised signal is high correlation with the original signal; it means that this method is suitable to remove the observation GPS noises. In addition, it can be seen that the maximum and minimum residuals between the original and de-noised signals are 11.86 and −3.63 cm, respectively. This indicated that the multipath errors of GPS signals are high. This error due to the base station is near to building, which contains the process monitoring system.

As well as, it can be seen that the de-noising processing caused an increased in the signals accuracy by 24%. The results have shown that noises can effectively be removed and the useful signals can be extracted from original signals with wavelet analysis as Fig. 4.

From Fig. 4, it can be seen that the X and Y-directions displacement of the tower show increase from starting the measurements at 0.00 (January, 10, 2008) to 10.00 (1.73, 1.60 cm) then decrease at 1.00 (January, 11, 2008) (−1.41,-1.04 cm). The same cycles were shows in another days 11 and 12 January 2008. In addition the maximum displacement becomes significant at 11.00 (January, 11, 2008) in X and Y-directions, 2.44, 1.76 cm, respectively, whereas, the minimum displacements are −1.66 and −1.50 cm in X and Y-directions respectively. Accordingly, it can be assumed that the tower displacement in two directions change in a similar manner. However, it can be concluded that the correlation between two directions are strongly influenced. It can be seen from Fig. 5 that the temperature increased and decreased random with the time, whereas, it can be show the maximum and minimum temperature are 0.80 °C and −8.76 °C at 2.00 and 20.00 (January, 12, 2008), respectively (Fig. 5a). In addition, the humidity can be assumed constant with the time observations, whereas shows increased at (18.00–20.00) in January, 10 (Fig. 5b). On the other hand, wind speed decreased from the starting to 11.00 (January, 11) then increased significantly till 12.00 January, 12 and decreased afterwards, as shown in Fig. 5d. Wind direction was between South East and North West during the observation period (150–350°) and mostly direction is South West (250°). The vehicle number, as shown in Fig. 5c, increased and decreased significantly with the displacement of tower in X and Y-directions. In addition, the time intervals for changes in the number of vehicles also coincided with the time intervals for the changes in the displacement X and Y-directions of the tower. However, it can be concluded that the main factor of displacements in X and Y-directions are the number of vehicle. Also, the wind may be affects on the displacement of two directions in the last day of observations.

4.2. Models identification results

Yonghe bridge will hereafter be referred to as "the system" in the identification study and the tower will be considered as the components of the system. Temperature (T), the number of vehicle on the bridge (V), the wind speed (W) and humidity (H) were chosen as the input quantities of the input signal, and the displacements in the X and Y-directions were chosen as the output quantities of the system. Robust fit regression and NNARMAX models were considered in the development of the transfer functions describing the relationship between the input and output quantities observed at tower. Transfer functions considered in expressing the relationship between the observed input and output quantities of the tower are illustrated in Fig. 6.

The bridge tower models have to be accurate and reliable and this depends on the accuracy and reliability of the observations used to define the model. The accuracy of the observations was checked with the instruments used. The accuracy of the instruments used can be shows in Section 2. The observations needed to be checked for outliers, where they increase the difficulty of defining the inherently complex NNARMAX models. So, the existence of outliers in the X and Y-directions were investigated in the definition phase of the robust fit regression model. The trend of the displacements recorded in the X and Y-directions were calculated in the initial phase of the model definition. Afterwards, the unknown parameters U^T of the robust regression model and the covariance matrices of these parameters were predicted using LS method. However, due to the sensitivity of the LS method to incompatible measurements, the existence of outliers was checked with bi-square weighted robust predictors. As a result of the investigation, w_i bi-square weights were found to be close, or near to "1" which showed that there were no outliers in the observations for the X and Y-directions. Therefore, model parameters for the tower displacements for X and Y-directions and their respective covariance matrices were predicted with bi-square weighted robust predictors. The results of this model were shown in Table 1 and Fig. 7. In addition, the model evaluation criteria; loss function λ_0, FPE and R-square values were calculated. The statistical significance of the model coefficients presented in Table 1 were tested by comparing them with the confidence boundary of the t-distribution related to the degree of freedom "f" at a confidence level of 95%, $t_{f,1-\alpha/2}$. Test results revealed that the coefficient pertaining to the temperature and humidity in the model 1 representing the displacements of the tower in the X and Y-directions were statistically insignificant since $t_{T,H} < 1.96$. Hence, the effect of temperature and humidity on the tower displacements in the X and Y-directions were ignored. Therefore, the models, model 2, used for calculating the tower displacements in the X and Y-direction were defined with respect to the variations in wind speed and the number of vehicles on the bridge (Table 1).

It can be seen in Table 1 that the λ_0, FPE and R-square values of the models describing the displacements of the tower in the two directions are nearly the same. This confirms that temperature and humidity has a negligible effect on the tower displacements in the two directions. As a result, the models used for calculating the tower displacements in the two directions were defined with respect to the number of vehicles on the bridge (V) and wind speed

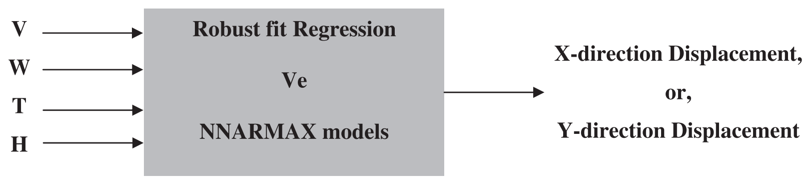

Fig. 6. Input–output quantities and models considered in the development of transfer functions for the Yonghe bridge tower.

Table 1
Robust fit model of the displacement of tower in X and Y directions with respect to the number of vehicle (V), wind speed (W), temperature (T), and humidity (H).

Model	Dis = $b0 + b1\,V + b2\,W + b3T + b4H$	$t_{(V,W,T,H)}$	λ_0	FPE	R^2
1	$X = -0.0168 + 0.00012V + 0.0018W - 6.4e{-}5T - 0.0010H$	18.08, 5.35, **−0.31**, −**2.80**	2.6e−5	2.7e−5	0.63
	$Y = -0.0112 + 9.8e{-}5V + 0.0011W + 0.00016T - 0.00069H$	17.45, 3.89, **0.93**, −**2.26**	1.7e−5	1.8e−5	0.62
2	$X = -0.0136 + 0.00012V + 0.0019W$	19.43, 5.85	2.6e−5	2.7e−5	0.62
	$Y = -0.0099 + 9.5e{-}5V + 0.0012W$	18.33, 4.45	1.7e−5	1.8e−5	0.61

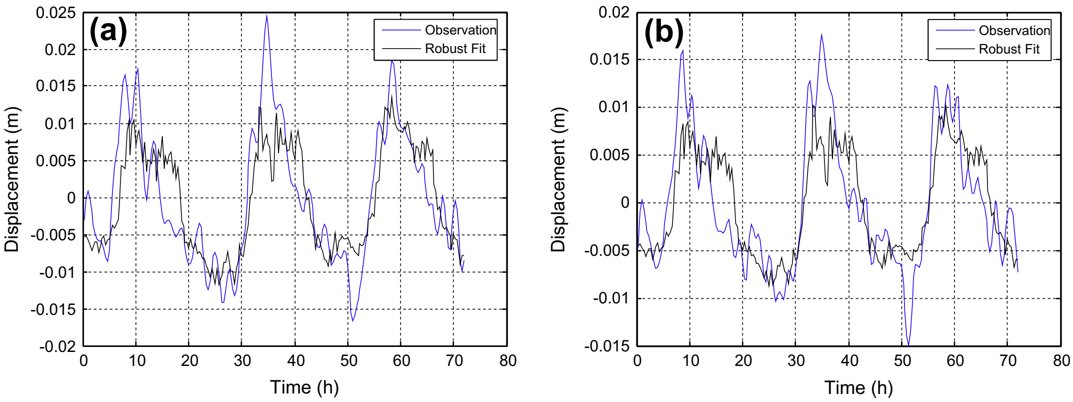

Fig. 7. Observation displacement and output produced by robust fit regression of southern tower in (a) X and (b) Y-directions.

change (W) (model 2). Robust predictors were used to check the existence of possible outliers in the observations and to identify the significant input parameters in the definition of multiple regression models for the X and Y displacements. In this type of models, there are no time lag between the inputs and outputs. Therefore, tower responds synchronously to the input quantity which is typical for static systems. Thus, it would not be incorrect to rephrase the robust multiple regression models as "static" robust multiple regression models. Furthermore, the values of the previous system inputs and outputs are not taken into account in this model. Static robust multiple regression models derived in this manner can be expressed with the n_a; n_b; n_c and n_k parameters of the NNARMAX model presented in Eqs. (5) and (6). Static robust multiple regression models used to define the displacements of the tower in this manner can be expressed with the NNARMAX [0100] model of $[n_a; n_b; n_c; n_k] = [0; 1; 0; 0]$. In this situation, robust static multiple regression models used to define the X and Y displacements of the tower have exogenous orders of $n_b = [1\,1]$, the past error $n_c = [0\,0]$ and time lags of $n_k = [0\,0]$ for auto-regressive order of $n_a = 0$ and the number of input variables of $n_u = 2$ (number of vehicles and wind speed).

NNARMAX models with the capability of taking into account the previous input–output and stochastic quantities and the time lag of the system were used to define the transfer functions of the tower displacements. These models can be quite difficult to set up when there is more than one input quantity. Insignificant input parameters and outliers in the observations significantly increase the difficulty of setting up the NNARMAX models. For this reason, results of the robust fit regression analysis were used to facilitate the definition of NNARMAX models of the tower displacements in Eq. (5). A number of NNARMAX models with different orders of complexity and time lags were considered in the selection of the proper order of complexity and time lag. Parameters of these models were predicted with the least square method. NNARMAX models with the minimum λ_0, FPE and maximum R-square values were selected as the proper models to express the tower displacements (Table 2).

Each of the models presented in Table 2 have different orders and time lags. In the selection process for the proper model for the tower, the residuals predictions of the models were tested to see whether they are within the ACF confidence interval. It was seen that the model corrections are within the ACF $\lambda(m)$ $(-u_{1-\alpha/2}\ s_{rm} < \lambda(m) < u_{1+\alpha/2}\ s_{rm})$ confidence interval (Fig. 9). ACF (for $m > 0$) has a normal distribution with an average value of zero and a standard deviation of $s_{rm} \approx 1/\sqrt{n} \cdot \alpha$ assumed significance level, $u_{1-\alpha/2}$ is the standard normal variable in the $1-\alpha/2$ probability. The ACF confidence interval for $\alpha = 0.05$ is $\pm 1.96/\sqrt{n}$. Here, n is the number of observations.

The displacement outputs of the NNARMAX models (Table 2) and the field observations of the tower displacements are presented in Fig. 8. It can be seen from these figures that the model outputs are very conformity with the field observations. ACF and 95% confidence intervals of the model residuals of NNARMAX describing the X and Y displacements of the towers are also presented in Fig. 9.

In the definition of the tower displacements of the Yonghe bridge with NNARMAX models, time lags were taken into account as well as the previous input and output quantities. These types of models reflect the definition of dynamic systems as "systems that store energy and release

Table 2
Parameters of NNARMAX models of the towers displacements in the X and Y-directions.

Displacement direction	NNARMAX $[n_a, n_b, n_c, n_k]$	λ_0	FPE	R^2
X	NNARMAX [4, 4 2, 1 2, 1 4]	1.83e−6	2.93e−6	0.90
Y	NNARMAX [5, 4 1, 1 1, 5 3]	1.67e−6	2.59e−6	0.86

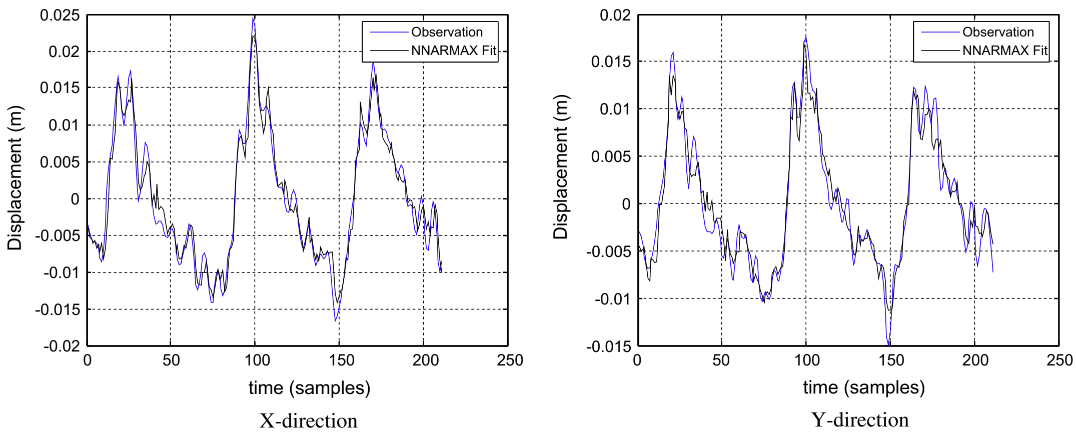

Fig. 8. Displacements output of the NNARMAX models for the tower displacements.

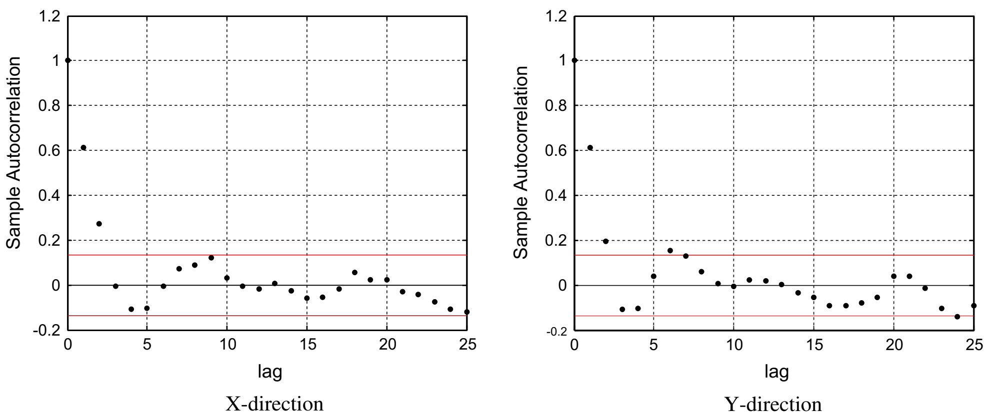

Fig. 9. ACF and 95% confidence intervals of NNARMAX models describing the displacements of the tower.

it over a time span''. Hence, the tower displacements of the bridge were modeled with NNARMAX models shown in Table 2 which have the capability of modeling dynamic response [10].

The ACF and 95% confidence intervals of the residuals for the NNARMAX models for two directions, which presented in Table 2 and the static robust multiple regression NNARMAX [0100] models used to describe to the displacements of the tower in the two directions. There were a loss of information in the static models describing the tower displacements in the two directions which can be calculated as the residuals of ACF of static NNARMAX [0100] models for the X and Y tower displacements were out of the confidence interval $\pm 1.96/\sqrt{n}$ for $\alpha = 0.05$. Residuals for the NNARMAX [4411] and [5415] models, however, remained in the boundaries of the ACF confidence interval and there was no loss of information in the description of the X and Y tower displacements as can be seen in Fig. 9. The fact that, λ_0, FPE and R-square values (Table 1) of the robust fit regression models are higher and less, respectively, than those of the NNARMAX models (Table 2), confirms the selection of NNARMAX for modeling the displacements response of the bridge towers.

5. Conclusions

In this study, we propose and analyze a MISO identification models, which are robust fit multiple regression and neural network ARMAX models. Based on this limited study, the analysis of the results leads to the following findings:

1. The proposed surveying techniques using RTK-GPS can provide valuable deformation data of the structural members.
2. GPS signals noise contains complex errors, and the signals accuracy obtained from the wavelet analysis (de-noised process) increased by 24%. So, it is recommended to use wavelet analysis in the de-noised of GPS signals.
3. The robust fit regression models have good capacities for mapping relationship of applied loads effects factors and displacements of tower. However, temperature and humidity effects on the entire modal shapes are insignificant.
4. The robust fit multiple regression results facilitated the definition of NNARMAX models of different orders and time lags.
5. It has been noted that the robust fit multiple regressions or NNARMAX [0 1 0 0] behave in a static manner which can lead to a loss of information to be used in calculating the tower displacements.
6. NNARMAX [4 4 1 1] and [5 4 1 5] models were found to be suitable for obtaining the tower displacements. In addition, no loss of information was observed since the residuals of these models stayed within the confidence intervals of the auto-correlation functions.
7. The predicted models reflect the behavior of the bridge tower displacements were a general increase in the number of vehicle on the bridge, however the traffic loads are the main factor displacements of tower.

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