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Nonlinear structural system wind load input estimation using the extended inverse method

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Abstract. This study develops an extended inverse input estimation algorithm with intelligent adaptive fuzzy weighting to effectively estimate the unknown input wind load of nonlinear structural systems. This algorithm combines the extended Kalman filter and recursive least squares estimator with intelligent adaptive fuzzy weighting. This study investigated the unknown input wind load applied on a tower structural system. Nonlinear characteristics will exist in various structural systems. The nonlinear characteristics are particularly more obvious when applying larger input wind load. Numerical simulation cases involving different input wind load types are studied in this paper. The simulation results verify the nonlinear characteristics of the structural system. This algorithm is effective in estimating unknown input wind loads.

Keywords: fuzzy estimator; fuzzy Kalman filter; least square method; fuzzy logic

1. Introduction

It is a very important task to clearly and effectively identity external interference in structural systems during strength, fatigue and reliability analyses. In general, identifying external forces is divided into direct and indirect methods. The direct method uses load transducers to measure the active reactions in a structural system. In practical engineering problems there are always difficulties in installing the load transducers used to measure unknown inputs. In the structural design and analysis, the loads caused by earthquakes and winds are both significant and need to be considered. There are many research works (Geurts and Bentum 2010, Li *et al*. 2010, Banik *et al*. 2010, Zhao and Ge 2010, Mara *et al*. 2010, Amoroso and Levitan 2011, Elshafey *et al*. 2011) devoted to structural design and analysis. Especially the strong wind causes severe vibration load to the building structure and makes the residents uncomfortable. In particular, the dynamic load is not easily obtained using direct measurements when a huge, transient loading is applied to the structural system. The inverse technique has been studied extensively using various techniques developed to address this issue (Yang and Yau 1997, Michaels and Pao 1985, Fabunimi 1986).

The inverse estimation method is a type of inverse technology widely adopted to cope with a system with inputs by measuring the structural system responses. There are recent researches on structural system input estimation. For example, Michaels and Pao (1985) presented a deconvolution iterative method that determines the orientation and time-dependent amplitude of

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the force emanating from the transient response of a plate surface at a minimum of two locations, with the source location given. Fabunmi (1986) presented a pseudo inverse technique to determine the effects produced on several structural modes due to vibratory forces. Hillary and Ewins (1984) utilized the least square technique to estimate the sinusoidal forces acting on both sides of a cantilever and used an experimental procedure to examine the estimation result. They applied this method to the impact load estimation of airplane turbine blades. Haung (2001) adopted the conjugate gradient method (CGM) to estimate the force of a one-dimensional mass-spring-damper structure with time-varying system parameters. Haung (2005) adopted the conjugate gradient method (CGM) to simultaneously estimate the unknown time-dependent external forces in a multiple-degree-of-freedom damped system. Quite good estimation results were presented in the above references. The related algorithms in the above references were all implemented in batch form. This kind of method is time-consuming and not an on-line procedure for the unknown input estimation.

To solve the above problems, Chen and Lee (2008) investigated an adaptive input estimation method applied to load input inverse estimation in a structural system. This method can be simply used to inversely estimate the input load using the dynamic response of the structural system. Good estimation results can be achieved; however, the estimates converge slowly in the initial state when the adaptive weighting function is used in the RLSE. The increase in process noise variance will influence the estimation precision. With a larger assumed process noise variance better time-varying force inputs tracking capability can be obtained, but the overall measurement noise reduction effectiveness will be degraded. Therefore, Chen *et al*. (2008) developed an intelligent fuzzy weighted estimator with higher target tracking performance and better noise reduction effectiveness. This estimator provided an efficient and robust estimation procedure for any unknown input situation; however, the overall measurement noise reduction effectiveness may be degraded when a larger initial process noise variance is assumed in the intelligent fuzzy weighted estimator. The estimates may be divergent in a high order of severity when an inappropriate initial process noise variance is assumed. In order to solve the above problem fuzzy logic inference fuzzy acceleration and weighting factors were proposed to enhance the estimator performance. They were successfully applied to estimate the input wind load of a structural system (Lee 2010). As opposed to the batch process the input estimation method uses the recursive form to process the data when dealing with more complex systems. There is no need to store all of the data to implement the process, reducing the quantity of necessary memory. The advantage was that higher effectiveness was achieved and the magnitude of the unknown could be estimated in time.

Most structural systems were assumed to be linear systems in the above mentioned references.In practical engineering problems the non-linear characteristics of a structural system are evident when a huge input load is applied on the structural system. Usually structural system non-linear characteristics will appear as various types and become more evident as the response amplitude changes rapidly. This study is the first application of this estimator to the unknown input wind load estimation of nonlinear structural systems. The proposed method is compared with other algorithms to verify its adaptability and robustness. The research results contribute to structural systems design and enhance design reliability. Because the proposed estimator uses a recursive calculation process, the dynamic input wind load can be estimated in real-time and used to exclude disturbances. This research may also provide important references for structural design or engineering applications. It can further be used as the basis of structural systems to improve seismic safety and early warning systems. In the future it could be extended to building and bridge disaster early warning systems.

2. Mathematical model

This study investigated non-linear effects when an unknown input load is applied to a tower structural system, as shown in Fig. 1. The unknown input wind load can be inverse estimated in real-time through the dynamic response of the measurement system. An intelligent adaptive fuzzy weighted extended inverse input estimation algorithm was used to effectively estimate the unknown input wind load of a nonlinear structural system. The tower structure is considered to be a non-linear lump-mass structural system with single degree of freedom (Ma and Ho 2004)

$$M\ddot{Y}(t) + F_r(\dot{Y}(t), \ddot{Y}(t)) = F(t) \tag{1}$$

where M is the effective mass. $Y(t)$ represents the displacement. $\dot{Y}(t)$ is the velocity. $\ddot{Y}(t)$ is the acceleration. $F_r(t)$ is the restoring force. $F(t)$ is the input wind load. For linear systems the restoring force can be expressed as a higher power function of the displacement and velocity, the viscous damping force and spring force are proportional to the speed and displacement (Masri and Caughey 1999).

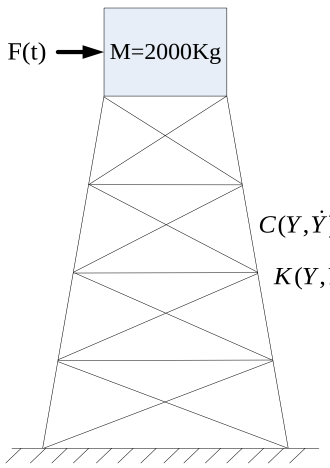

Fig. 1 Model of the tower structural system

Assuming the relationship between the restoring force parameters, displacement and velocity can be expressed using the nonlinear variable damper model, that is, the restoring force magnitude can be expressed as an approximate one square and cubic function of the displacement and velocity (Osinski 1998)

$$F_r = k_1 Y(t) + k_2 Y^3(t) + c_1 \dot{Y}(t) + c_2 \dot{Y}^3(t) \tag{2}$$

where k_1, k_2, c_1 and c_2 are constant. The movement Eq. (1) can be rewritten as follows

$$m\ddot{Y}(t)+k_1Y(t)+k_2Y^3(t)+c_1\dot{Y}(t)+c_2\dot{Y}^3(t)=F(t) \tag{3}$$

The input estimation algorithm is a calculation method using the state space. First let $X(t)=\begin{bmatrix}Y(t) & \dot{Y}(t)\end{bmatrix}^T$, then Eq. (3) can be rewritten as follows

$$\dot{X}_1 = X_2$$
$$\dot{X}_2 = \frac{F(t)}{M} - \frac{c_1}{M}X_2 - \frac{c_2}{M}X_2{}^3 - \frac{k_1}{M}X_1 - \frac{k_2}{M}X_1{}^3$$

The movement equation can be expressed as a non-liner state equation

$$\dot{X}(t) = f(X,F) \tag{4}$$

The above movement equation is converted to state space. Linearization and discretization for the continuous-time state equation and measurement equation, estimates the unknown input wind load using an extended inverse input estimation algorithm with intelligent adaptive fuzzy weight.

3. Extended Kalman filter

The basic extended Kalman filter concept was proposed by Schmidt. It is an extension of the Kalman filter applied to nonlinear dynamic systems (Mendel 1995). Simply said, linearization for a nonlinear dynamic system model estimates the system using the Kalman filter. Extending the Kalman filter is also a robust modeling approach resistant to white noise interference. This method has been widely used in various science and engineering fields (Hiroshi *et al*. 2002).

In order to coordinate computing the state space method the above movement equation can be converted to the state-space model using $X=\begin{bmatrix}Y(t) & \dot{Y}(t)\end{bmatrix}^T$. The continuous-time state equation and structural system measurement equation can be formulated as follows

$$\dot{X}(t) = f(X,F) \tag{5}$$

$$Z(t) = HX(t) = h(X) \tag{6}$$

Taking the structural system processing noise into consideration, Linearization and discretization for the continuous-time state Eq. (5), the discrete-time statistic model of the state equation is shown below

$$X(k+1) = \Phi X(k) + \Gamma(F(k)+w(k)) \tag{7}$$

where

$$X(k) = \begin{bmatrix}X_1(k) & X_2(k) & \cdots & X_n(k)\end{bmatrix}^T$$

$$\Phi = I + \frac{\partial f(X^*(K),F^*(k))}{\partial X}\Delta t,$$

$$\frac{\partial f(X^*(K),F^*(k))}{\partial X}=\begin{bmatrix} 0 & 1 \\ -\frac{k_1}{M}-3\frac{k_2}{M}X_1{}^2 & -\frac{c_1}{M}-3\frac{c_2}{M}X_2{}^2 \end{bmatrix}$$

$$\Gamma=\frac{\partial f(X^*(K),F^*(k))}{\partial F}\Delta t,$$

$$\frac{\partial f(X^*(K),F^*(k))}{\partial F}=\begin{bmatrix} 0 \\ \frac{1}{M} \end{bmatrix}$$

$$w(k)=\begin{bmatrix} w_1(k) & w_2(k) & \cdots & w_n(k) \end{bmatrix}^T,$$

$$F(k)=\begin{bmatrix} F_1(k) & F_2(k) & \cdots & F_n(k) \end{bmatrix}^T$$

$X(k)$ is the state vector. Φ is the state transition matrix. Γ is the input matrix. Δt is the sampling interval. $w(k)$ is the processing error vector, which is assumed as Gaussian white noise.

Note that $E\left\{w(k)w^T(j)\right\}=Q\delta_{ij}$. Q is the discrete-time processing noise covariance matrix. δ_{ij} is the Kronecker delta function. $X^*(k),F^*(k)$ is the nominal state, calculated by the extended Kalman filter prediction equations. As a result the discrete-time statistic model of the measurement vector can be presented below

$$Z(k+1)=HX(k+1)+v(k+1) \tag{8}$$

where

$$H=\frac{\partial h(X^*(k),F^*(k))}{\partial X}\Delta t,$$

$$Z(k)=\begin{bmatrix} Z_1(k) & Z_2(k) & \cdots & Z_n(k) \end{bmatrix}^T,$$

$$v(k)=\begin{bmatrix} v_1(k) & v_2(k) & \cdots & v_n(k) \end{bmatrix}^T,$$

$Z(k)$ is the observation vector. $v(k)$ represents the measurement noise vector and is assumed to be Gaussian white noise with zero mean and the variance $E\left\{v(k)v^T(j)\right\}=R\delta_{ij}$. R is the discrete-time measurement noise covariance matrix. H is the measurement matrix. After deriving the linearized dynamic nonlinear structural system equations the Kalman filter calculation rule can be used to estimate the state. It can achieve the purpose of extending the Kalman filter. The bias innovation is produced using the estimation and measurement values. The magnitude of the unknown input wind load can be estimated using the recursive least squares method.

4. Intelligent fuzzy weighting input estimation method

According to the linearization and discretization for the state and measurement equations, the magnitude of the unknown input wind load can be estimated using the system response measurement value using the input estimation theory. For nonlinear structural systems the input estimation method consists of two parts; the first is the extended Kalman filter without inputs and the second is the on-line intelligent fuzzy weighting least square algorithm. The extended Kalman filter equations without inputs are as follows (Ma and Ho 2004)

$$\bar{X}(k/k-1) = \bar{X}(k-1/k-1) + \int_{t=(k-1)\Delta T}^{k\Delta T} f(\bar{X}(k-1/k-1), k-1)dt \tag{9}$$

$$\Phi = I + \frac{\partial f(\bar{X}((k-1/k-1), k-1)}{\partial X}\Delta T \tag{10}$$

$$\Gamma = \frac{\partial f(\bar{X}((k-1/k-1), k-1)}{\partial F}\Delta T \tag{11}$$

$$H = \frac{\partial h(\bar{X}((k-1/k-1), k-1)}{\partial X}\Delta T \tag{12}$$

$$P(k/k-1) = \Phi P(k-1/k-1)\Phi^T + \Gamma Q \Gamma^T \tag{13}$$

$$\bar{Z}(k) = Z(k) - H\Phi\bar{X}(k-1/k-1) \tag{14}$$

$$S(k) = HP(k/k-1)H^T + R \tag{15}$$

$$K_a(k) = P(k/k-1)H^T S^{-1}(k) \tag{16}$$

$$P(k/k) = [I - K_a(k)H]P(k/k-1) \tag{17}$$

$$\bar{X}(k/k) = \Phi\bar{X}(k/k-1) + K_a(k)\bar{Z}(k) \tag{18}$$

The on-line intelligent fuzzy weighting least square algorithms are as follows (Ma and Ho 2004)

$$B_s(k) = H[\Phi M_s(k-1) + I]\Gamma \tag{19}$$

$$M_s(k) = [I - K_a(k)H][\Phi M_s(k-1) + I] \tag{20}$$

$$K_b(k) = \gamma^{-1}(k)P_b(k)B_s^T(k)\left[\gamma^{-1}(k)B_s(k)P_b(k-1)B_s^T(k) + S(k)\right]^{-1} \tag{21}$$

$$P_b(k) = \gamma^{-1}(k)[I - K_b(k)B_s(k)]P_b(k-1) \tag{22}$$

$$\hat{F}(k) = \hat{F}(k-1) + K_b(k)\left[\bar{Z}(k) - B(k)\hat{F}(k-1)\right] \tag{23}$$

where $S(k)$ is the residual covariance. $\bar{Z}(k)$ is the bias innovation produced by the measurement noise and input disturbance. $K_b(k)$ is the correction gain. In addition, $B_s(k)$ and

$M_s(k)$ are both the sensitivity matrices. $P_b(k)$ is the error covariance of the input estimation process. $\hat{F}(k)$ is the estimated unknown inputs. γ is the weighting factor. The weighting factor in this search is proposed based on the fuzzy logic inference system.

The basic fuzzy logic system configuration considered in this paper is illustrated here. The fuzzy logic system includes four basic components; the fuzzy rule base, fuzzy inference engine, fuzzifier and defuzzifier. The fuzzy logic system input value, $\theta(k)$, may be chosen in the interval, $[0,1]$. The Pythagorean theorem with the transverse axle (time, *t*) and the vertical axle (residual of predictor, $\bar{Z}$) can be used to solve the hypotenuse length. In other words, the hypotenuse length is the variation rate in the residual in the sampling interval. The dimensionless input variable is defined as follows

$$\theta(k) = \frac{\left|\frac{\Delta\bar{Z}(k)}{\bar{Z}(k)}\right|}{\sqrt{\left(\frac{\Delta\bar{Z}(k)}{\bar{Z}(k)}\right)^2 + \left(\frac{\Delta t}{t_f}\right)^2}} \tag{24}$$

where $\Delta\bar{Z}(k) = \bar{Z}(k) - \bar{Z}(k-1)$. Δt is the sampling interval, let $t_f = 1$. The proposed intelligent fuzzy weighting factor uses the input variable $\theta(k)$ to self-adjust the $\gamma(k)$ factor in the recursive least square estimator. Therefore, the fuzzy logic system consists of one input and one output variable. The input value, $\theta(k)$, may be chosen in the interval, $[0,1]$, and the output value, $\gamma(k)$, may also be in the interval, $[0,1]$. The fuzzy sets for $\theta(k)$ and $\gamma(k)$ are labeled in EP (extremely large positive), VP (very large positive), LP (large positive), MP (medium positive), SP (small positive), VS (very small positive), and ZE (zero) linguistic terms. The specific membership is defined using the Gaussian functions shown in Fig. 2.

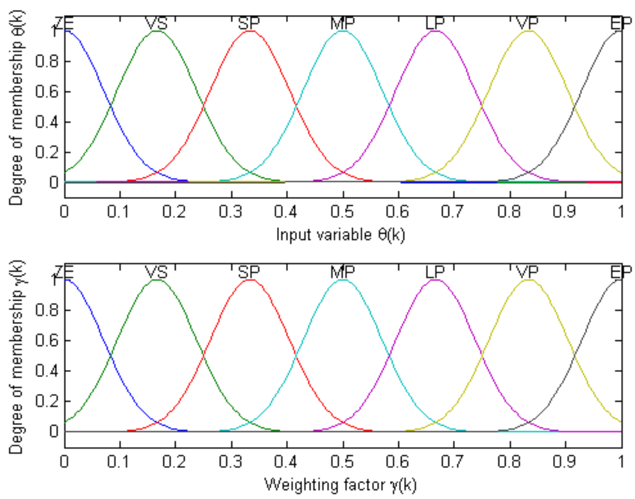

Fig. 2 Membership functions of the fuzzy sets for $\theta(k)$ and $\gamma(k)$

A fuzzy rule base is a collection of fuzzy IF-THEN rules:

IF $\theta(k)$ is zero (ZE) THEN $\gamma(k)$ is an extremely large positive (EP),

IF $\theta(k)$ is a very small positive (VS) THEN $\gamma(k)$ is a very large positive (VP),

IF $\theta(k)$ is a small positive (SP) THEN $\gamma(k)$ is a large positive (LP),

IF $\theta(k)$ is a medium positive (MP) THEN $\gamma(k)$ is a medium positive (MP),

IF $\theta(k)$ is a large positive (LP) THEN $\gamma(k)$ is a small positive (SP),

IF $\theta(k)$ is a very large positive (VP) THEN $\gamma(k)$ is a very small positive (VS),

IF $\theta(k)$ is an extremely large positive (EP) THEN $\gamma(k)$ is zero (ZE),

where $\theta(k) \in U$ and $\gamma(k) \in V \subset R$ are the input and output of the fuzzy logic system, respectively. The fuzzier maps a crisp point $\theta(k) \in U$ into a fuzzy set A in U. Therefore, the non-singleton fuzzifier can be expressed in (Wang 1994)

$$\mu_A(\theta(k)) = \exp\left(-\frac{\left(\theta(k) - \bar{x}_i^l\right)^2}{2\left(\sigma_i^l\right)^2}\right) \tag{25}$$

$\mu_A(\theta(k))$ decreases from 1 as $\theta(k)$ moves away from $\bar{x}_i^l$. $\left(\sigma_i^l\right)^2$ is a parameter characterizing the $\mu_A(\theta(k))$ shape.

The Mamdani maximum-minimum inference engine is used in this paper. The fuzzy implication max-min-operation rule is shown in (Wang 1994)

$$\mu_B(\gamma(k)) = \max_{j=1}^{c}\left\{\min_{i=1}^{d}\left[\mu_{A_i^j}(\theta(k)), \mu_{A_i^j \to B^j}(\theta(k), \gamma(k))\right]\right\} \tag{26}$$

where *c* is the fuzzy rule and *d* is the input variables dimension.

The defuzzifier maps a fuzzy set B in V to a crisp point $\gamma \in V$. The fuzzy logic system with the center of gravity is defined in (Wang 1994)

$$\gamma^*(k) = \frac{\sum_{l=1}^{n} \bar{y}^l \mu_B\left(\gamma^l(k)\right)}{\sum_{l=1}^{n} \mu_B\left(\gamma^l(k)\right)} \tag{27}$$

n is the number of outputs. $\bar{y}^l$ is the value of the l th output. $\mu_B\left(\gamma^l(k)\right)$ represents the membership of $\gamma^l(k)$ in the fuzzy set B. Substituting $\gamma^*(k)$ of Eq. (27) in Eqs. (21) and (22) allows us to configure an adaptive fuzzy weighting function of the recursive least square estimator (RLSE).

5. Results and discussion

A nonlinear tower structural system example is simulated to verify the practicability and precision of the presented approach in estimating the unknown input wind load, as shown in Fig. 1. Assuming a centralized structural system mass, *m* = 2000 kg. The restoring force is, such as Eq.

(2), where $c_1 = k_1 = 0.015$, $c_2 = k_2 = 0.0001$. The input wind load is modeled using a cycle sine type; therefore, Eq. (3) can be rewritten as follows

$$2000\ddot{Y}(t) + 0.015Y(t) + 0.0001Y^3(t) + 0.015\dot{Y}(t) + 0.0001\dot{Y}^3(t) = A_m \sin \omega t \tag{28}$$

where $A_m = 500$ and $\omega = 10$ denote the amplitude and frequency of the harmonic input wind load, respectively. The tower structure was assumed as a single degree of freedom lumped mass nonlinear structural system. Substituting dynamic response (displacement) into the input estimation method, a numerical simulation of the input wind load inverse estimation of the structural system can be presented. The process noise and measurement noise are considered first in the simulation process. The process noise covariance matrix, $Q_w = Q \times I_{2n\times 2n}$, where $Q = 10^{-6}$.

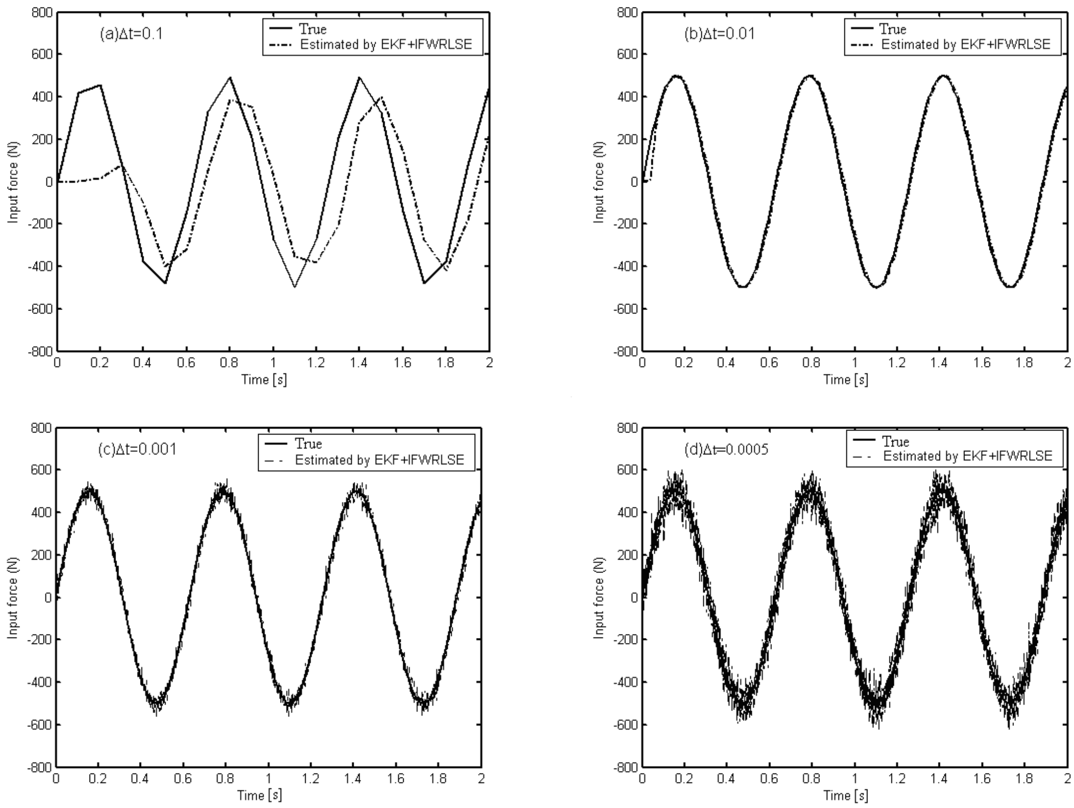

Fig. 3 Comparison of the estimation results using different sampling time

The measurement noise covariance matrix, $R_v = R \times I_{2n\times 2n}$, where $R = \sigma^2 = 10^{-10}$. The algorithm includes the extended Kalman filter (EKF) without inputs and the intelligent fuzzy weighted recursive least squares estimation (IFWRLSE). The simulation and estimation parameters are as follows: The initial conditions are given as $P(0/0) = diag\left[10^4\right]$, $\hat{F}(0) = 0$ and $P_b(0) = 10^8$. The sensitivity matrix $M(0)$ is null. The weighting factor is an intelligent fuzzy weighting function. The estimation results are further compared by alternating between the constant and adaptive weighting factors. The estimation results produced by using different sampling intervals are shown in Fig. 3. The four chosen sets of sampling intervals are Δt =0.1, 0.01, 0.001 and 0.0001sec. The estimation results are acceptable when the sampling time, $\Delta t <$ 0.001sec, such as in Figs. 3(b), 3(c) and 3(d). Fig. 3(b) shows that the tracking capability is enhanced when the Δt =0.01 sampling interval is adopted. However, the estimator exhibits poor convergence in the initial simulation step. The tracking capability is enhanced. Fig. 3(d) shows that the estimator can still work without divergence in the estimation process when the Δt =0.0001s sampling interval is adopted. However, the fluctuation becomes more severe. In order to take the estimation precision and calculation time of the estimator into account, the Δt =0.001s sampling interval is chosen to implement the simulation in this study.

Fig. 4 shows the intelligent fuzzy weighted input estimator results with the process noise variance fixed at ($Q = 10^{-6}$), the sampling interval, Δt =0.0001s and with different measurement error variances ($R = 10^{-10}$ and 10^{-9}). This result shows that when R is small the estimator transient performance will be better against the noise effect. On the other hand the fluctuation will become more severe when R increases. The estimator transient performance will be poorer with more influence induced by noise. A smaller R indicates that the measurement is more precise. The effort made to obtain a more precise measurement will be higher.

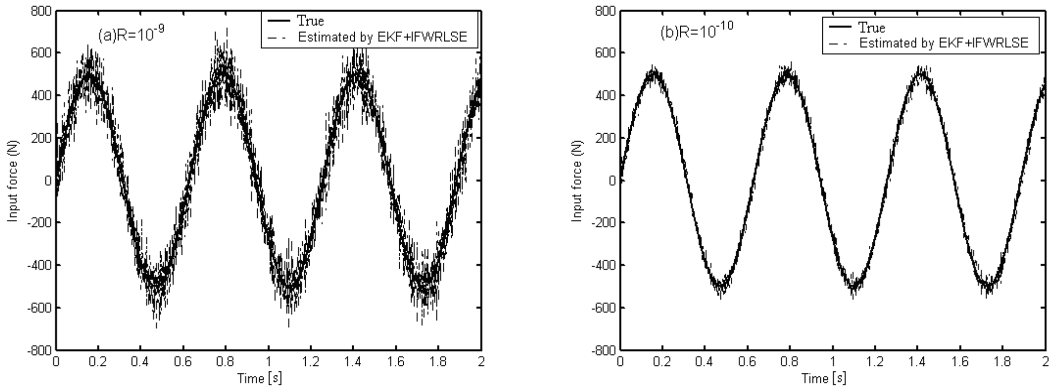

Fig. 4 Comparison of the estimation results using different measurement errors

Fig. 5 shows the estimation results when adopting different weighting factors with the process noise variance fixed at ($Q = 10^{-6}$), the sampling interval, Δt =0.0001s and with measurement error variances ($R = 10^{-10}$). An intelligent fuzzy weighted and adaptive weighting factor, despite leading to a better transient performance and tracking ability, makes the estimator subject to fluctuations due to unwanted system noise. On the other hand the estimator is less sensitive to disturbances with a constant value $\gamma = 0.95$ and 0.75, but has relatively poorer transient performance and overall tracking capability. The intelligent fuzzy weighted input estimator and adaptive weighting factor estimator have better target tracking capability and noise reduction effectiveness after all.

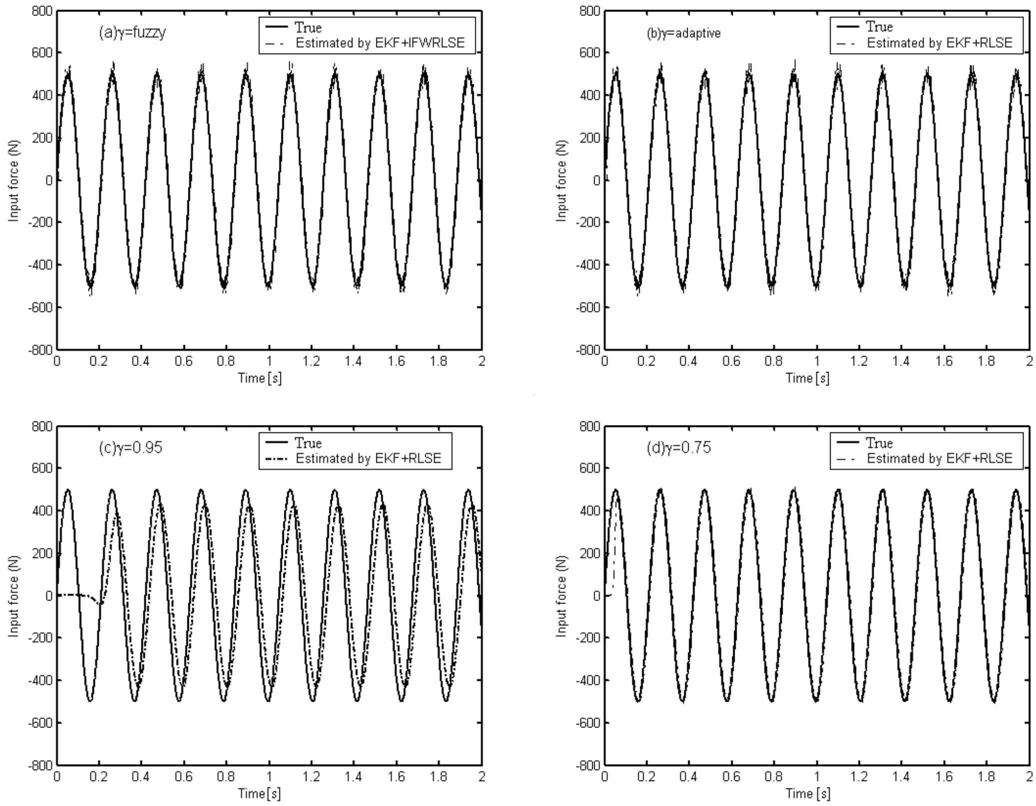

Fig. 5 Comparison of the estimation results using different weighting factors

To further illustrate the accuracy and robustness of the proposed estimator, increasing the input frequency was considered to explore the simulation estimation results. Fig. 6 shows the estimation results with process noise variance fixed at ($Q = 10^{-6}$), measurement error variances ($R = 10^{-10}$) and the sampling interval, Δt =0.001s. When the wind input frequency was changed to $F(t) = 500 \times \sin(20t)$ (N), the input frequency conditions increased, allowing the estimator to inverse estimate the unknown input effectively with acceptable estimation results. Under the same simulation conditions the wind input frequency was increased to $F(t) = 500 \times \sin(30t)$ (N), achieving good estimation results as Fig. 7.

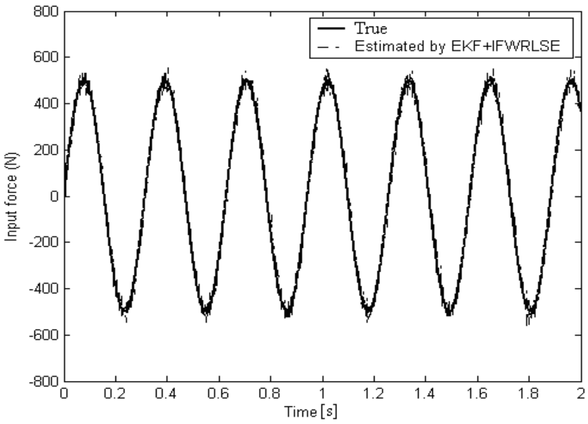

Fig. 6 The estimation result using the input frequency, $F(t) = 500 \times \sin(20t)$ (N)

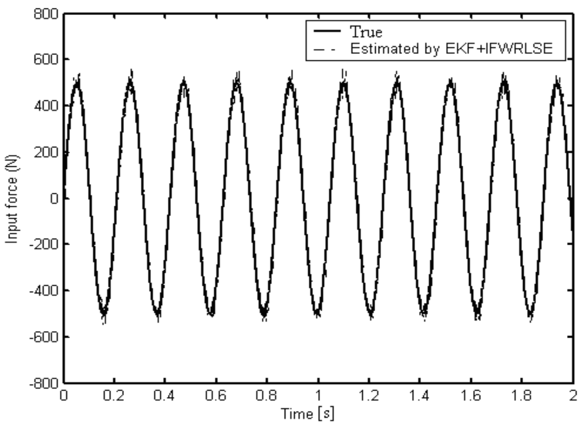

Fig. 7 The estimation result using the input frequency, $F(t) = 500 \times \sin(30t)$ (N)

In the practical processing environment, the loads, such as water, wind, and the earthquake loads, to the structure system are mostly irregular or random. Therefore, to explore the random load estimation is absolutely necessary. The mathematical formula of the random wind load inputs applied to the tower structure is shown as $F(t) = 200 \times random$ (N). By applying the active reaction which contains noise to the input estimation algorithm, the estimation result of the random load inputs can be determined as in Fig. 8. The figure shows the comparison between the true load values and the estimates on a tower structure. Fig. 8(b) shows the local enlarged estimation results. The tracking capability of the estimator is weak to peak value of the load inputs.

Overall, the input estimation method verification process proposed in this research considers both the effects caused by the modeling noise and the measurement noise. The above simulation results demonstrate that the proposed method performs better than other algorithms. The overall estimation performance is just fine. In the course of estimating the random load inputs, the tracking capability of the estimator is getting weak due to the severe variation of the wind load inputs, and the time delay is caused.

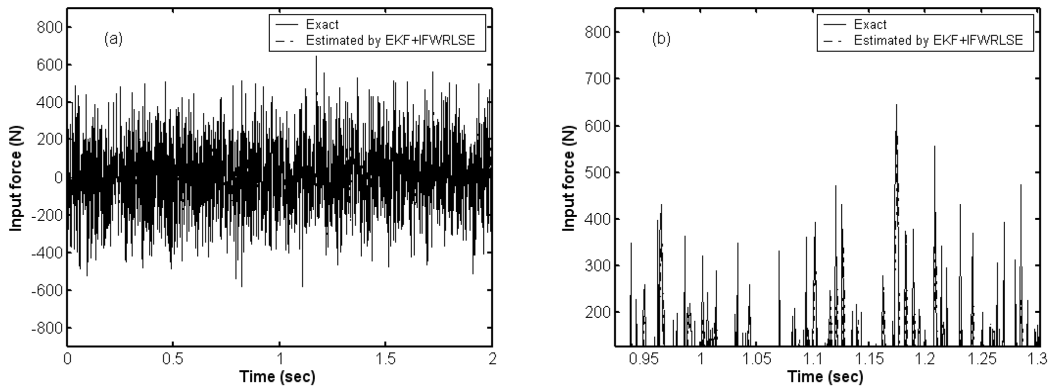

Fig. 8 The estimation result using the random inputs, $F(t) = 200 \times random\ (N)$

6. Conclusions

This paper presented an intelligent fuzzy weighted input estimation method applied to estimate the unknown input wind load on a tower nonlinear structural system. The method combined the Extended Kalman Filter with the intelligent fuzzy weighted least square algorithm to estimate the input wind load. The simulation cases demonstrated the feasibility and practicality of the proposed method. The modeling and measurement noise and different input frequency were considered in the estimation process. The proposed method was proven effective in estimating the unknown input. The proposed method was further compared by alternating between the adaptive weighting and constant factors to demonstrate its excellent performance. This method is very simple and can be applied to two and three-dimensional structural systems and optimal control problems.

Acknowledgments

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