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# Bridge Scour Monitoring using Extended Kalman Filter

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**ABSTRACT**

Scouring of bridge foundation is one of the major causes of bridge failure. Scour can be defined as the excavation of foundation or other material from the bed and banks of streams, due to water flow. Scour monitoring is a major requirement to ensure bridge safety. Direct scour measuring instruments such as float-out and radar devices are costly and difficult to maintain. An alternative is vibration-based monitoring techniques that monitor the change in modal properties to identify scour. These methods suffer from low Sensitivity of modal properties to scour depth. This paper proposes a scour monitoring method using Extended Kalman Filter (EKF) that uses time history responses in conjunction with a structural model to identify the scour depth with better accuracy. Foundation stiffness of piers being the most sensitive parameter to scouring, this parameter is estimated using the EKF algorithm that operates with limited response measurements and intact finite element model of piers. The developed method is validated numerically.

**KEYWORDS:** *Scour monitoring, Pier, Extended Kalman filter.*

## 1. INTRODUCTOIN

Various studies in the field of bridge safety and maintenance proves that foundation scour is the major cause for bridge failure (Briaud et al., 1999). Normal water flow on riverbed takes long time to cause a significant scouring but during a flood event, scouring is rapid and may lead to sudden collapse. Thus scour monitoring is highly important to ensure the bridge safety. Scour is removal of river bed materials like sand and rocks. This process around piers and abutments leads to failure of piers which intern causes bridge collapse. Scour can be classified into three type's viz. natural / general scour, contraction scour and local scour. Natural scour is considered as aggradation and degradation of bed materials in the absence of obstacles (Federico et al., 2003). Contraction scour occurs due to manmade constructions such as piers and abutments in river which reduces the cross-sectional area and increases the shear stress and flow velocity in that section. When the shear stress exceeds the bed's threshold, contraction scour occurs (Briaud et al., 1999). Fluid structure interaction between pier and stream (see Fig. 1) causes removal of bed materials around individual piers and abutments. This type of scour is called local scour (Hamill, 1999).

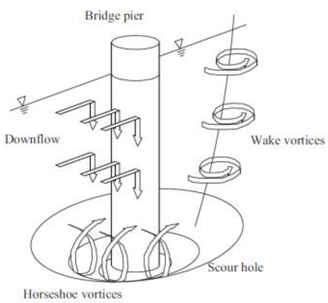


Figure 1.1 schematic of local scour (Prendergast and Gavin 2014)

Usually visual inspection is carried out to check scour depth. Major disadvantages of visual inspection is it cannot be carried out during flooding, when the risk of scour is high. Scour depth may not be identified when scour hole is filled with flood water subsides (Lin et al., 2010; Foti and Sabia, 2011). Alternative approaches are to use depth measuring instruments such as single use devices (Briaud et al., 2011), Pulse or radar devices (Hussein, 2012), Fiber-Bragg grating (May et al., 2002), Buried rods (Zarafshan et al., 2012), sound wave devices (Anderson et al., 2007) and electrical conductivity devices (Anderson et al., 2007). Most of these devices require underwater installation, which can be costly and prone to get damaged. To overcome these disadvantages researchers proposed vibration based scour monitoring techniques (Foti and Sabia, 2011; Brincker et al., 2001). Removal of materials on foundation causes reduction in foundation stiffness which in turn changes the modal properties of the structure (See Fig. 1.2). Accelerometers are generally used to track the change in modal properties (natural frequency) with a reference Finite Element (FE) model. The sensitivity of modal properties to scour depth is low and temperature change also effects the modal properties of pier. Thus monitoring the modal properties are unreliable.

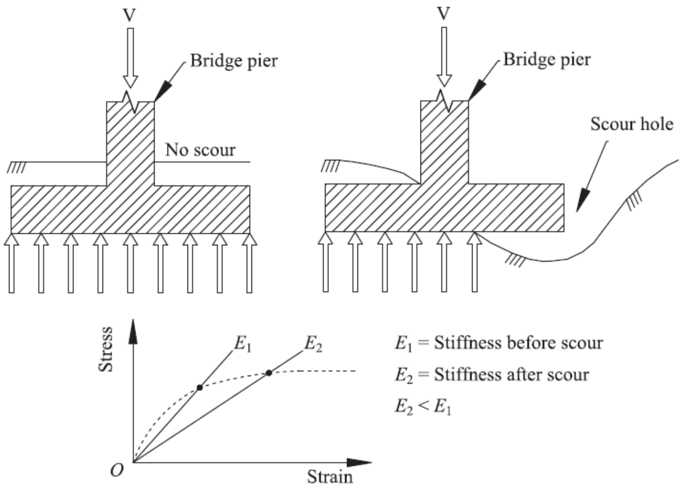


Figure 1.2 Reduction in stiffness caused by scour (Prendergast and Gavin 2014)

This paper also uses dynamic measurements to estimate the scour depth. Here time history of dynamic measurements are used unlike the modal properties. Extended Kalman filter along with an intact FE model is used to track the changes in foundation stiffness. Each samples in time history is used to update the foundation stiffness in a recursive manner. This method is illustrated and validated numerically in the following sections. Section 2 explains the general EKF algorithm. Section 3 illustrates the technique of scour monitoring using EKF and validating it numerically.

## 2. EXTENDED KALMAN FILTER

Kalman filter was developed by Kalman (1960), which is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. The extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance.

To explain the principle and procedure of EKF, We first consider a general dynamic system whose nonlinear state space equation with added noise is described as follow:

$$\dot{x} = f(x(t)) + w(t) \tag{2.1}$$

where *w(t)* represents the process noise with covariance $\boldsymbol{Q}$. The nonlinear observation equation at time $t = k$ can also be expressed as

$$y_k = h(x(t)) + v(t) \tag{2.2}$$

where *v(t)* shows the measurement noise with covariance $\boldsymbol{R}$. Eq. 2.1-2 can be rewritten in discrete form as

$$x_{k+1} = F(x_k) + w_k \tag{2.3}$$
$$y_k = h(x_k) + v_k \tag{2.4}$$

Function $F$ can be obtained by integrating Eq. 2.1.

$$F(x_{k+1}) = x_k + \int_{k\Delta t}^{(k+1)\Delta t} f(x_k(t))dt \tag{2.5}$$

In the extended Kalman filter method, an initial estimate of the system's state is predicted and then updated using observed measurements.

*State Prediction:*
Mean and covariance of states are predicted as.

$$\hat{x}_{k+1}^{-} = x_k + \int_{k\Delta t}^{(k+1)\Delta t} f(x(t))dt \tag{2.6}$$

$$\boldsymbol{P}_{k+1}^{-} = \emptyset_{k+1}\boldsymbol{P}_k\emptyset_{k+1}^{T} + \boldsymbol{Q}_k \tag{2.7}$$

where, $\emptyset$ is the linearized state transition matrix, expressed as

$$\emptyset_{k+1} = I + \Delta t\left[\frac{\partial f(x(t))}{\partial x(t)}\right]_{x(t)=\hat{x}_k^{-}} \tag{2.8}$$

Measurement prediction

$$\hat{y}_{k+1} = h(\hat{x}_{k+1}^{-}) \tag{2.9}$$

*Measurement update:*
Mean and covariance are updated as follows.

$$\hat{x}_{k+1} = \hat{x}_{k+1}^{-} + \boldsymbol{K}_{k+1}(y_{k+1} - \hat{y}_{k+1}) \tag{2.10}$$

$$\boldsymbol{P}_{k+1} = [\boldsymbol{I} - \boldsymbol{K}_{k+1}\boldsymbol{H}_{k+1}]\boldsymbol{P}_{k+1}^{-}[\boldsymbol{I} - \boldsymbol{K}_{k+1}\boldsymbol{H}_{k+1}]^{\boldsymbol{T}} + \boldsymbol{K}_{k+1}\boldsymbol{R}_{k+1}\boldsymbol{K}_{k+1}^{T} \tag{2.11}$$

where, $\boldsymbol{K}_{k+1}$ is the Kalman gain

$$\boldsymbol{K}_{k+1} = \boldsymbol{P}_{k+1}^{-}\boldsymbol{H}_{k+1}[\boldsymbol{H}_{k+1}\boldsymbol{P}_{k+1}^{-}\boldsymbol{H}_{k+1} + \boldsymbol{R}]^{T} \tag{2.12}$$

where, $\boldsymbol{H}_k$ is the linearized coefficient matrix of observation equation

$$\boldsymbol{H}_{k+1} = \left[\frac{\partial h(x)}{\partial(x)}\right]_{x=\hat{x}_{k+1}^{-}} \tag{2.13}$$

Note Eq. 2.8 is first order approximation of non-linear system. When the system is highly non-linear this approximation may lead to poor estimation. In such cases higher order approximation should be used or Unscented Kalman Filter algorithms (Wan and Van der Merwe, 2000) can be employed to handle highly non-linear system.

## 3. SCOUR IDENTIFICATION USING EKF

From section 2, EKF shows the capability to handle nonlinear state space models. With this property EKF is widely used in the field of nonlinear state estimation. This section explains how EKF is used in scour monitoring. As explained in section 1, scouring affects the foundation stiffness of pier which in turn changes its vibration characteristics. In the state space model, the foundation stiffness to be monitored are modelled as one of the states among velocities and displacements. This process makes the system non-linear. This nonlinear state space model is processed with EKF algorithm and states are updated to reduce the error between predicted and measured responses. Foundation stiffness are also updated during this process, which indirectly measures the scour depth. Following sub-sections brief the numerical model and its non-linear state space equations.

### 3.1. FE model with scour

A simple Finite Element model of Bridge pier is shown in this section. Fig. 3.1 shows the FE modeling of pier. Six beam elements of length 0.25 m are used to model the pier. The element has a rectangular cross-section of 1 cm thickness and 2 cm width. Young's modulus and density of the material where selected as 206 Gpa and 7850 kg/m$^3$. The mass of deck is replaced with the mass 'M', bearing stiffness is represented by 'K2' in the FE model. First two elements are assumed to be foundation elements. Compaction from soil to foundation is modelled with horizontal springs {k}. Stiffness of horizontal springs are increased towards the root of pier. In this example three horizontal springs have stiffness of 20, 40 and 50 N/m towards the root respectively. Removing these horizontal springs helps to imitate various sour situation. In this example, removal of first horizontal spring represent initial sour where scour depth is 0.25 m and two springs are removed to imitate large scour case (see Fig. 3.1). Zero-mean random input is applied to the node above foundation.

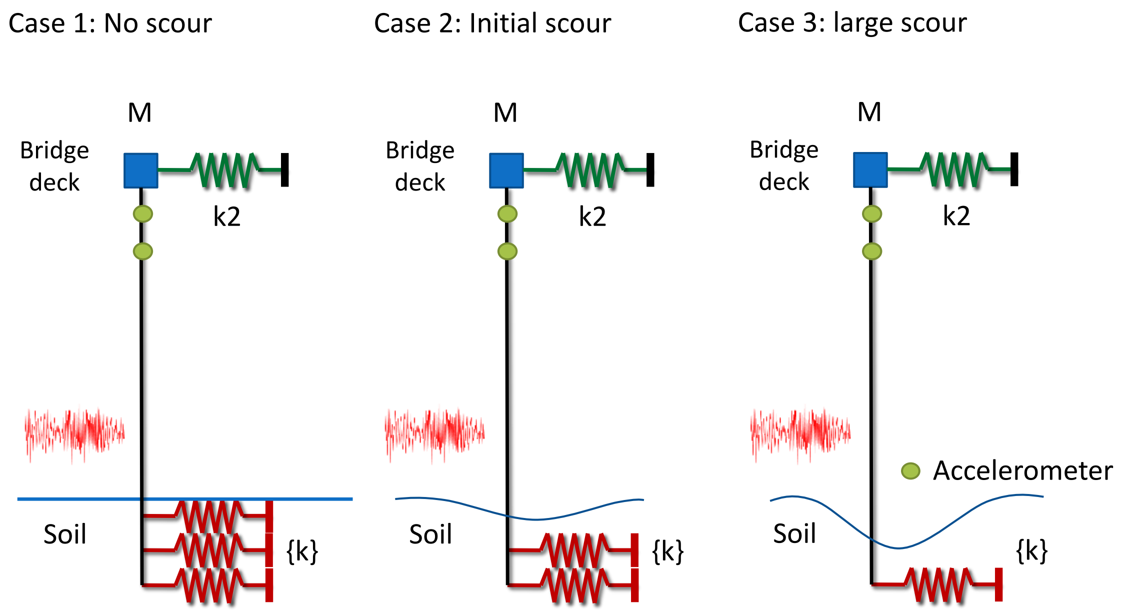


Figure 3.1 Finite Element Mode for various scour situation

### 3.2 Non-linear state space model

This section introduces linear state space system and moves to Non-linear state space model of the considered pier model. Equation of motion of a linear dynamic system is given. Input is assumed only form process noise.

$$\mathbf{M}\ddot{u}(t) + \bar{\boldsymbol{C}}\dot{u}(t) + \boldsymbol{K}u(t) = 0 \quad (3.1)$$

where, *u(t)* is the displacement; it's time derivatives $\dot{u}(t)$ and $\ddot{u}(t)$ are velocity and acceleration vectors, respectively; $\boldsymbol{M}$, $\bar{\boldsymbol{C}}$, and $\boldsymbol{K}$ are the mass, damping and stiffness matrices of the dynamic system, respectively.

Let *x(t)* be the state vector given as

$$x(t) = \begin{Bmatrix} u(t) \\ \dot{u}(t) \end{Bmatrix} \quad (3.2)$$

Then, equation of motion is expressed in the linear state-space form as

$$\dot{x}(t) = \boldsymbol{A}x(t) + \boldsymbol{G}w(t) \quad (3.3)$$
$$y(t) = \boldsymbol{C}x(t) + \boldsymbol{H}w(t) + v(t) \quad (3.4)$$

where, $\boldsymbol{A}$ and $\boldsymbol{B}$ are the system matrices. Matrix $\boldsymbol{C}$ in Eq. 3.2.4 is selected depending on the output of interest *y(t)*; Process and measurement noises *w(t)* and *v(t)* are assumed to be stationary, mutually uncorrelated stochastic process following the normal probability distribution. $w \sim \mathrm{N}(0,\boldsymbol{Q})$ and $v \sim \mathrm{N}(0,\boldsymbol{R})$ respectively; the matrices $\boldsymbol{G}$ and $\boldsymbol{H}$ are the coefficients of process noise.

Since the foundation stiffness {k} should be monitored, {k} is made as one of the states among displacement and velocity vectors. Now the state vector is give as

$$x(t) = \begin{Bmatrix} u(t) \\ \dot{u}(t) \\ \{k\} \end{Bmatrix} \tag{3.5}$$

From Eq. 3.5 the augmented stiffness vector {k} into state vector makes the system nonlinear. State space representation of non-linear system is shown

$$\dot{x} = f(x(t)) + w(t) \tag{3.6}$$
$$y_k = h(x(t)) + v(t) \tag{3.7}$$

where, the non-linear function *f(x(t))* is given as

$$f\big(x(t)\big) = \begin{bmatrix} 0 & I & 0 \\ -\boldsymbol{M}^{-1}\boldsymbol{K}(\{k\}) & -\boldsymbol{M}^{-1}\overline{\boldsymbol{C}} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{Bmatrix} u(t) \\ \dot{u}(t) \\ \{k\} \end{Bmatrix} \tag{3.8}$$

Eq. 3.6-7 are similar to Eq. 2.1-2 in section 2. Thus the nonlinear state space model can be solved and their states including foundation stiffness are updated using EKF algorithm.

## 3.3 Result

This section numerically validates EKF based scour identification technique. From the previous discussions, the EKF algorithm update the state values (including foundation stiffness) to minimize the mean of squared error between measured and predicated responses. EKF algorithm requires intact FE model and limited response. In this example two acceleration response near deck is collected (see Fig. 3.1). Limited responses for various scoured situations are simulated using MATLAB Simulink.

Figure 3.2-4 shows the foundation stiffness estimated for various sour cases. Note that the initial assumption of the foundation stiffness values is taken corresponding to non-scoured situation (see Fig. 3.2-4). EKF algorithm estimates the actual foundation stiffness form the measured limited responses. From Fig. 3.2 the estimated stiffness lies closer to the initial assumed stiffness which means that there is no scour and no change in the foundation stiffness. In case 2 (see Fig. 3.3) stiffness estimation of the first horizontal spring is reduced to 0 KN/m, which shows the compaction provided by first spring to pier is zero. This clearly indicates the presence of scour with a scour depth of 0.25m. The corresponding change in natural frequency is 0.06 Hz which is very small to identify. In case 3 (see Fig. 3.4) first two horizontal springs stiffness are reduced to 0, which indicates a scour depth of 0.5 m. Shift in natural frequency for this case is 0.12 Hz. The swift in natural frequency is very small and thus EKF based method is more reliable.

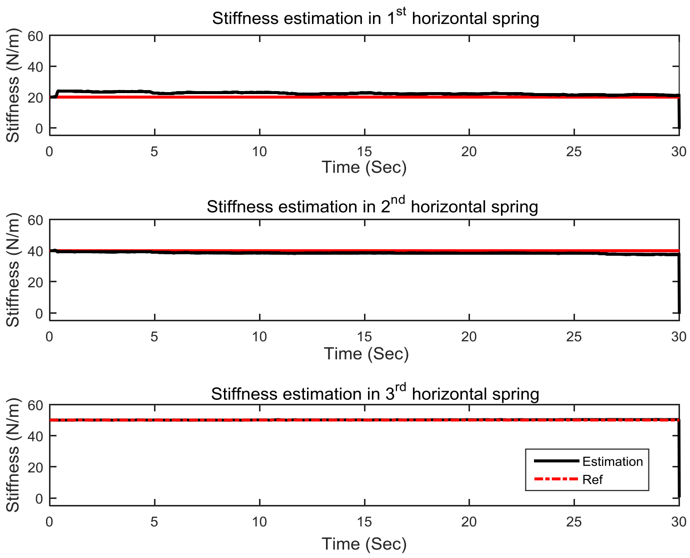


Figure 3.2 Case 1: no scour

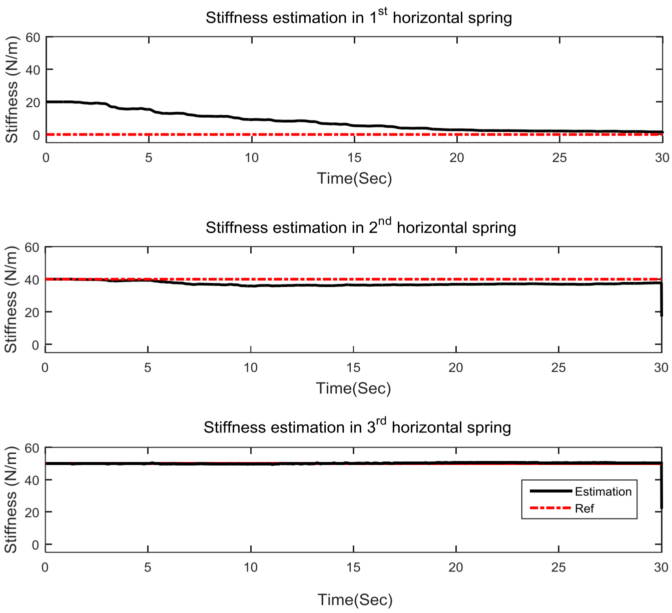


Figure 3.3 Case 2: initial scour

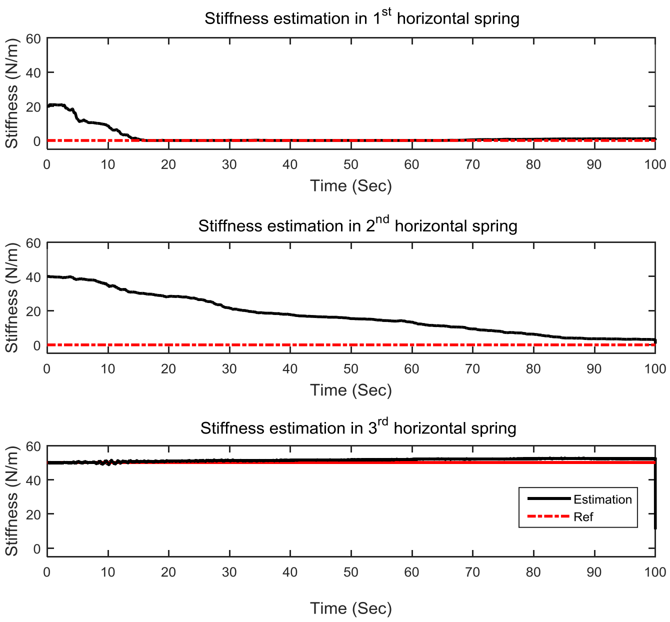


Figure 3.4 Case 3: large scour

## 5. CONCLUSION

The basic idea of scour and the requirements for scour monitoring are studied. Further the study presented in this paper briefs the procedure of EKF algorithm and shows the technique to adopt EKF in scour identification. Scour depth estimation has been successfully validated with a simple pier model. Numerical validation proves EKF based method is more reliable compared to other vibrations based methods. This method is yet to be tested with full-scale pier model and with more realistic input situations. The EKF algorithm linearize the non-linear system at each step and so the accuracy of estimation is less while using a complex pier model. To overcome this issue Unscented Kalman Filter (UKF) algorithm can be employed to improve the estimation accuracy over a complex model.

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