A Stochastic Framework Considering Uncertainties of Scouring on the Stability of Bridges

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ABSTRACT Scouring around bridge foundations is a critical phenomenon in civil engineering which involves the erosion of sediment around piers due to flowing water, posing significant threats to bridge stability worldwide. In this context, understanding and addressing uncertainties in scouring processes are pivotal for developing robust predictive models, enhancing infrastructure resilience, and ensuring the safety and longevity of bridges. The uncertainties in scouring arise from complex interactions of various factors such as flow characteristics, sediment properties, bridge geometry, and environmental conditions. In this context, river flow values are expected to increase in some regions under a changing climate, posing significant uncertainties. This paper highlights the uncertainties in scouring estimation and explores the challenges in understanding the dynamic nature of scouring, emphasizing the lack of complete knowledge and the inherent variability in real-world conditions. This paper also proposes an innovative method of estimating the scour taking into account the variability and uncertainties of the scour phenomenon. This method is based on stochastic processes capable of simulating the accumulation and the back-filling of scour holes, followed by integrating artificial intelligence to predict scour depth estimates under a changing climate.

Keywords Stochastic process, Uncertainties, Scouring, Climate Change, Artificial Intelligence.

I. INTRODUCTION

The lack of precise knowledge in comprehending the multifaceted aspects influencing a phenomenon poses challenges in the domains of prediction, risk assessment, and decision-making. Uncertainties can arise from intricate processes and interactions within complex systems, natural variability, and human factor errors. In this context, estimating local scour, which refers to the erosion of the river bed material around bridge piers due to river flow, is a complex task associated with several uncertainties, i.e., hydraulic conditions, sediment properties, river geometry, estimation methods, and climate change.

Estimation scour mainly relies on empirical equations that were developed from laboratory and site observations with specific conditions, in which extrapolating these models to different site conditions introduces uncertainties. Scour estimation empirical models have evolved over the past decades. In this context, the HEC-18 design manual is the most commonly used model in estimating the scour depth (Richardson and Davis, 1995), the model was developed by the Colorado State University from laboratory data and is recommended by the United States Department of Transportation's Hydraulic Engineering (Arneson et al., 2012). There are significant discussions among researchers about the overestimation of the local scour estimates (Chase and Holnbeck, 2004; Kassem et al., 2003; Wang et al., 2023). This overestimation is based on the coefficients applied by the model considering the pier shape, riverbed material size and morphology, and angle of flow.

Climate change refers to significant and long-term lasting alterations in the Earth's climate patterns, including shifts in temperatures, precipitation patterns, and other climatic variables. The uncertainties in forecasting the Earth's system arise from the simulations' variability, emission scenarios, resolution, and societal responses (Habeeb and Bastidas-Arteaga, 2022). This is illustrated by the complexity in representing and simulating the interactions between the processes of the Earth's system and the uncertainties in projecting human activities and their impact on the climate system. Noteworthy, is the effectiveness of society in applying adaptation solutions and mitigation efforts, which introduces uncertainties related to decision-making. For example, the Paris Agreement stated that the average annual temperature anomalies relative to the pre-industrial era should be less than 2 degrees by 2050 (UNFCCC, 2018).

This paper presents a comparative analysis of local scour estimates around piers by comparing the local scour estimates from the HEC-18 design guideline with 98 site measurements and proposes a framework to stochastically simulate and predict the scour estimates. The objectives of this paper are as follows:

- Investigating the uncertainties associated with scour estimates.
- Setting up the foundation for an innovative stochastic framework capable of simulating and predicting the accumulation and back-filling of scour holes.

II. METHEDOLOGY

A. Scour uncertainties

A comparative analysis allows for identifying the patterns and trends of several factors (angle of flow, bed condition, bed material size, and bed material type) influencing the overestimation of local scour estimates across different cases of local scour. This analysis compares the local scour estimated from the HEC-18 design guideline with 98 site measurements from 12 sites (Table 1) to illustrate the degree of uncertainties of scour estimates by considering several criteria as follows:

- Investigating the uncertainties within all sites to present a general overview of uncertainties for each site.
- Investigating the uncertainties based on bed material types within all sites.
- Investigating the uncertainties based on bed material size and angles of flow within specific sites to eliminate the impact of other factors.

TABLE 1. Characteristics of sites.

Sites	ID	Material type	Material size (mm)	Angle of flow	Pier shape
Susitna	A	Cobbles	70	0°	Sharpe
Tazlina	B	Cobbles	90	0°	Round
Knik	C	Gravel	5	0°	Sharpe
Snow	D	Gravel	7.6	0°	Round

Rio Grande	E	Gravel	29.8	26°,36°	Sharpe
Tye	F	Gravel	72	0°	Round
White	G	Gravel	0.64, 1.19	0°,5°,10°	Round
Arkansas	H	Sand	0.64, 1.19	0°,12°,19°	Round
Eel	I	Sand	0.5	0°	Round
Pearl	J	Sand	0.54	8°,11°,14°,16°,18°,23°,28°	Round, Square
Knik	K	Sand	0.58, 1.8	0°	Round
Pamunkey	L	Sand	0.7	0°	Round

The error indicators are measures to highlight the presence of errors and deviations by comparing the scour estimates and scour measurements. In this context, the Mean Error (ME) indicator refers generally to the overall bias of the overestimation or underestimation between the estimates and the measurements.

$$ME = \frac{\sum_{i=1}^{n}(Y_i - X_i)}{n} \tag{1}$$

where Y_i are the scour estimates, X_i are the scour site measurements, and n is the number of measurements.

The Root Mean Square Error ($RMSE$) indicator provides a measure of accuracy by measuring the average magnitude of the differences between the estimates and the measurements.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(Y_i - X_i)^2}{n}} \tag{2}$$

The Mean Absolute Error (MAE) indicator provides the arithmetic average of the absolute differences between the estimates and measurements, irrespective of the direction of the errors. It serves as a measure of presenting the central tendency of the errors, providing a straightforward assessment of the magnitude of deviations.

$$MAE = \frac{\sum_{i=1}^{n}|Y_i - X_i|}{n} \tag{3}$$

B. Scour stochastic simulation and predicting

The stochastic method of simulating the scour (Eq. (4)) considers the evolution of consistent accumulation of scour by a progressive process $S_{PP}(t)$ (Eq. (5)), higher scour deviations from the trend that are controlled by the rate of occurrence of a pre-determined shock sizes $S_{SP}(t)$ (Eq. (6)), and back-filling of scour hole which is presented by an annealing process $S_{AP}(t)$ (Eq. (7)). The stochastic scour estimates $S_s(t)$ are given by:

$$S_s(t) = S_{PP}(t) + S_{SP}(t) + S_{AP}(t) \tag{4}$$

The progressive process of scour (Eq. (5)) simulates the positive trend and the accumulation over time. This process is a continuous-time process with stationary and independent increments, in which the increments are a large number of small accumulations governed by a mean value μ_{BM} and standard deviation σ_{BM}. The accumulated scour depth S_{PP} is given by:

$$S_{PP}(t) = \sum_{i=1}^{t} \mu_{BM}(t) + \sigma_{BM} W(t),\ W \sim N(\mu_W, \sigma_W) \tag{5}$$

where W is a standard Brownian Motion with mean $\mu_W = 0$ and standard deviation $\sigma_W = 1$.

The shock process (Eq. (6)) is a continuous time stochastic Compound Poisson Process with shock sizes ζ_i, this process simulates the higher magnitudes of scour deviating from the accumulated positive trend (Eq. (5)) and is controlled by the rate of occurrence $\in [0, \infty]$ of pre-determined shock sizes with mean value μ_{CPP} and standard deviation σ_{CPP}, in which a Poisson Process defines the number of shocks Nt in [0,t]. The shock scour depth estimates S_{SP} is given by:

$$S_{SP}(t) = \sum_{i=1}^{N_t} \zeta_i\,, \qquad \zeta_i \sim N(\mu_{CPP}, \sigma_{CPP}) \tag{6}$$

The annealing process (Eq. (7)) simulates the back-filling of a scour hole by applying a recovery model ξ_i that is exponentially distributed. The parameter of the recovery model α is the result of an optimization function solving the difference between two sequential states, in which the number of arrivals M_t in $[0, t]$ is controlled by the rate of occurrences $\in [0, \infty]$ of pre-determined back-filling magnitudes following a Poisson Process. The back-filled scour depth is given by:

$$S_{AP}(t) = \sum_{i=1}^{M_t} -\xi_i\,, \qquad \xi_i = e^{\alpha} \tag{7}$$

This is followed by integrating artificial intelligence (Multilayer Feed-Forward Neural Network) to predict the time series scour depth estimates (Hyndman et al., 2021). This method is relevant since it considers the evolution of time series data by integrating an autoregressive process of order p with non-linear functions. In this context, local scour-lagged time series estimates are the inputs x to the neural network and are given by:

$$x = x_{t-1}, x_{t-2}, x_{t-3}, \dots, x_{t-p} \tag{8}$$

Neurons within the hidden layer capture the patterns by computing the weighted sum of the inputs, where each input is multiplied by a corresponding weight. The neurons n_i are defined by:

$$n_i = \sum_{i=1}^{N_n} w_i x_i + \propto_i \tag{9}$$

where N_n is the number of input layer neurons, w_i is the weight assigned to the i^{th} hidden neuron, x_i is the set of inputs for each neuron, and $\propto_i$ is the intercept for each hidden neuron. In this context, each node applies an activation function $f(n)$ of non-linear binary sigmoid function to the weighted sum from the preceding layer and is given by:

$$f(n) = \frac{1}{1 + e^{-n}} \tag{10}$$

III. RESULTS AND DISCUSSIONS

A. Scour uncertainties

The uncertainties of scour estimates from the HEC-18 design manual are presented by a comparative analysis with 98 scour site measurements from 12 sites. This analysis investigates the impact of the angle of flow, bed morphology, bed material size, and bed material type on the magnitude of uncertainties. The uncertainties of local scour estimates for each site in Table 2 provide a general overview of the uncertainties for different site conditions. The results indicate a high deviation in the uncertainties of scour magnitudes between the sites due to the variations in the site conditions and variables influencing the scour magnitudes.

TABLE 2. Error indicators for each site.

Sites		RMSE (m)		MAE (m)		ME (m)	
ID	No. of measures	LL	UL	LL	UL	LL	UL
A	8	0.70	2.48	0.62	2.40	0.51	2.40
B	2	1.44	6.78	1.44	6.77	1.44	6.77
C	1	0.66	3.44	0.66	3.44	0.66	3.44
D	1	0.08	1.12	0.08	1.12	0.08	1.12
E	3	1.19	3.75	1.18	3.71	1.18	3.71
F	6	0.40	0.74	0.39	0.71	0.39	0.71
G	6	0.54	2.16	0.48	2.13	0.48	2.13
H	10	0.49	1.70	0.46	1.61	0.43	1.61
I	2	0.23	0.53	0.21	0.53	-0.10	0.53
J	12	1.07	3.67	0.89	3.38	0.89	3.38
K	19	0.41	1.57	0.37	1.49	0.18	1.44
L	28	0.27	0.41	0.24	0.36	-0.03	0.35

Investigating the uncertainties of scour magnitudes associated with bed material characteristics (Table 3) offers valuable insights into understanding the general influence of bed material types on the variability of scour magnitudes. The results indicate a lower degree of uncertainty is associated generally with bed material type of sand, gravel, and cobbles, respectively.

TABLE 3. Uncertainties associated with bed material characteristics.

Bed material type	RMSE (m)		MAE (m)		ME (m)	
	LL	UL	LL	UL	LL	UL
Cobbles	0.90	3.76	0.79	3.27	0.70	3.27
Gravel	0.66	2.26	0.56	1.92	0.56	1.92
Sand	0.55	1.85	0.41	1.35	0.24	1.34

Investigating the influence of the bed material sizes on the uncertainties of scour magnitudes is a critical aspect in understanding the dynamics of the scour phenomenon since the size of the bed material plays an important role in determining the erosive forces due to flowing water. This study includes presenting the error indicators (Table 4) and the distribution of errors following the quartile method (Figure 1) for the Knik site (ID: K), given its extensive data associated with two distinct bed material sizes. The results indicate a lower degree of uncertainty for the lowest-size material. However, it is noteworthy to highlight the presence of a notable deviation.

TABLE 4. Uncertainties associated with bed material size.

Bed material size	RMSE (m)		MAE (m)		Standard deviation	
	LL	UL	LL	UL	LL	UL
1.8 (mm)	0.37	1.70	0.33	1.68	0.29	0.28
0.58 (mm)	0.52	1.12	0.49	0.98	0.51	0.81

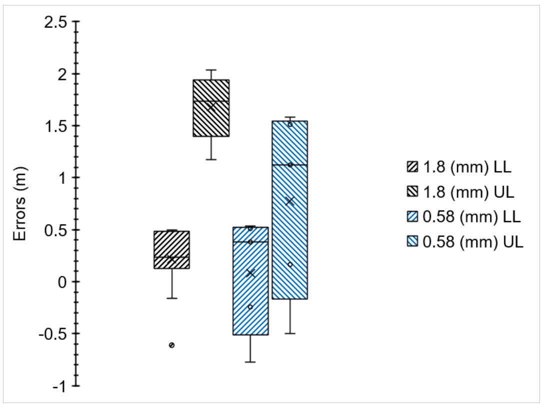


FIGURE 1. Uncertainties distribution associated with size variation.

Investigating the uncertainties associated with different flow angles (Figure 2) across two sites, White and Pearl, offers valuable insights into the influence of diverse hydraulic conditions while maintaining consistent round pier shape, bed morphology, and bed material. The findings indicate heightened uncertainties correlated with larger flow angles.

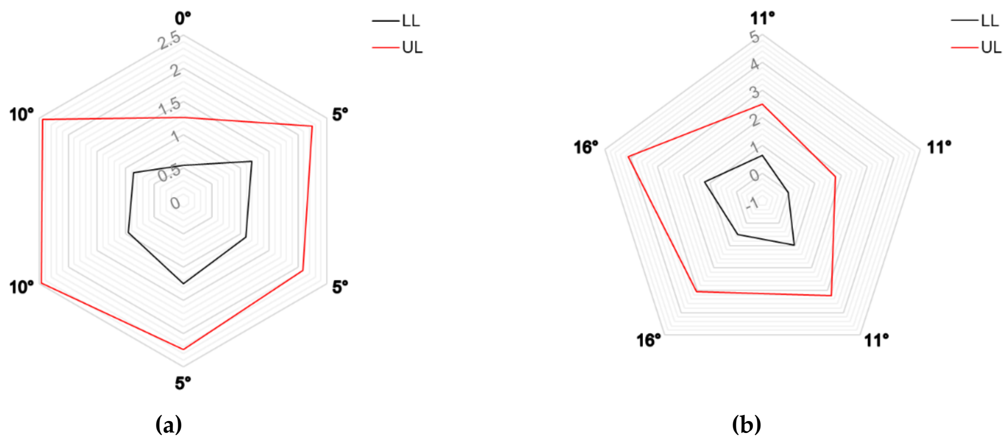


FIGURE 2. **Uncertainties associated with angles of flow. (a) White site, (b) Pearl site.**

B. Scour stochastic simulation and predicting

The stochastic simulations present the behavior of scour, i.e., accumulation (progressive and shock) and back-filling (annealing). In this context, the stochastic scour (Eq. (4)) simulates a hypothetical input of scour depth values (Figure 3) which was suggested to clearly indicate the behavior of scour.

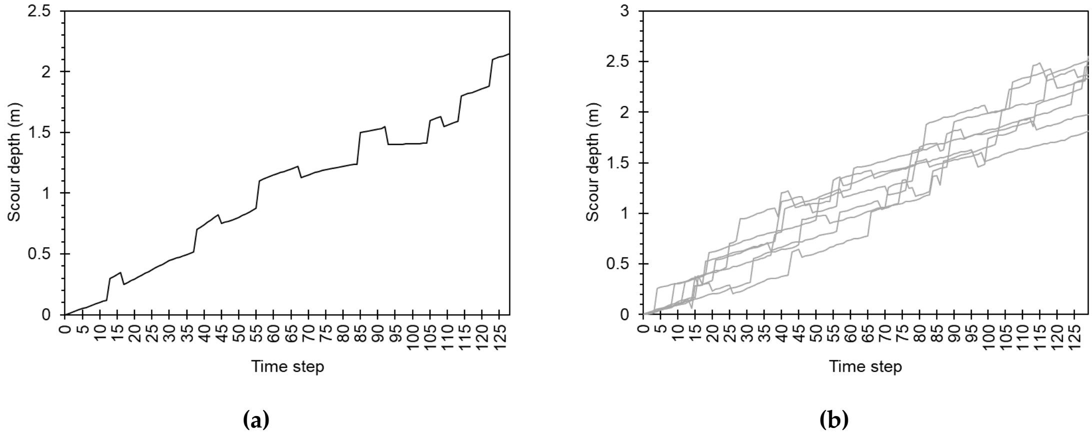
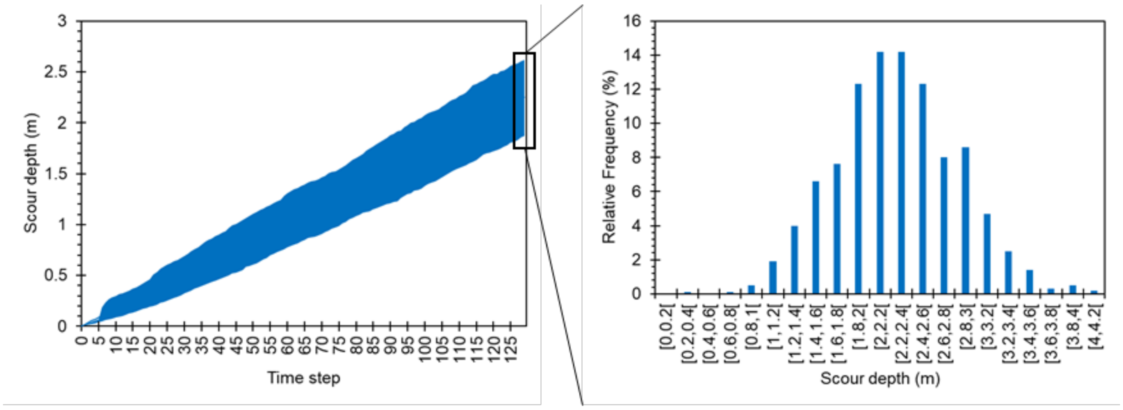


FIGURE 3. **Scour depth. (a) Hypothetical data, (b) Example of 7 stochastic simulations.**

Figure 4 presents the general distribution of the stochastic simulations (LL and UL) and the last time step distribution to indicate the variability and characteristics of the simulated data. The results indicate that the highest frequency of stochastic scour depth corresponds to the maximum value of the hypothetical data.



(a) **(b)**

FIGURE 3. **Stochastic simulations. (a) Distribution-Quartile limits, (b) Histogram.**

The error indicators derived from the stochastic simulations (Table 5) indicate a noteworthy level of accuracy in the simulations' results, in which the distribution of errors (Figure 4), presents an overview visualization of the central tendency and the spread of errors.

TABLE 5. Error indicators of stochastic simulations.

RMSE (m)		MAE (m)		ME (m)	
LL	**UL**	**LL**	**UL**	**LL**	**UL**
0.21	0.39	0.17	0.34	-0.17	0.34

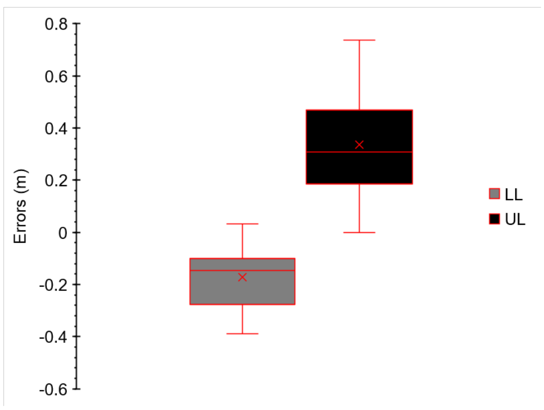


FIGURE 4. Errors distribution of the stochastic simulations.

The predictions of scour derived from the Multilayer Feed-Forward Neural Network, consider the evolution of the limits (UL and LL) of stochastic time series scour estimates beyond the 68th time step by integrating an autoregressive process. Figure 5 indicates the comparison between the scour predictions and the actual stochastic scour estimates. The results indicate minimal deviations and high accuracy, in which the mean absolute percentage of errors of the forecasts is less than 5% which is considered an indication of high accuracy forecasts.

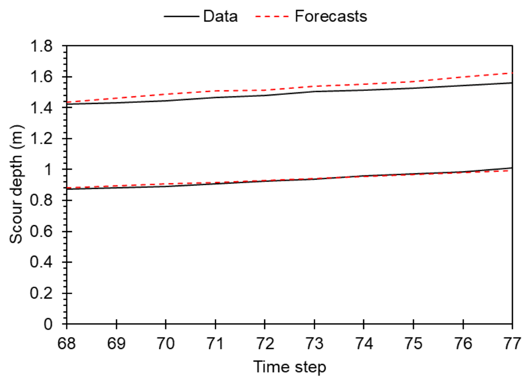


FIGURE 5. **Forecasts of stochastic scour estimates.**

IV. CONCLUSIONS

This paper investigates the uncertainties associated with local scour estimates from HEC-18 design guidelines by presenting a comparative analysis with site measurements, in addition, this paper proposes a stochastic framework capable of simulating and predicting local scour. The main conclusions are summarized as follows.

- The variations of site conditions influence the scour magnitudes. As a results, the uncertainties of scour estimates are inconsistent, impacting the safety factor within the design phase of a bridge, and therefore, posing a higher risk to the stability of the bridge or higher infrastructure costs.
  - In this study, a high deviation is detected in the uncertainties of scour magnitudes between all the sites, and therefore, the authors suggest interpreting machine learning to the historical scour data for each site to handle the complexity of the relationships between the variables influencing the scour magnitudes within each site.
  - In this study, a lower degree of uncertainty is associated generally between all the sites following the bed material type sand, gravel, and cobbles, respectively.
- The variations of each site scour influencing factors impact the magnitudes of uncertainties. In this context, understanding these variations is essential for developing comprehensive and effective strategies to ensure structural safety.
  - In this study, the influence of the bed material sizes within the Knik site (ID: K), given its extensive data associated with two distinct bed material sizes, indicates a lower degree of uncertainty for the lowest-size material.
  - In this study, the influence of angles of flow is investigated across two sites, White and Pearl, maintaining consistent round pier shape, bed morphology, and bed material. The findings indicate heightened uncertainties correlated with larger flow angles.

- Stochastic framework of simulating and predicting local scour, captures the inherent variability and uncertainties associated with local scour by introducing probabilistic predictions into the modeling framework.
    - In this study, the uncertainties within the stochastic simulations of scour are less deviation in terms of error indicators when compared to those of the scour estimates.
    - In this study, a Multilayer Feed-Forward Neural Network presented high-accuracy forecasts of stochastic simulations with a mean absolute percentage of errors value less than 5% which is considered an indication of high-accuracy forecasts.

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