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Honghui Fan
Sichuan College of Architectural Technology

Wei Xiang (✉ 313896617@qq.com)
Sichuan College of Architectural Technology

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Time-series Uncertainty Quantification of Foundation Settlement with Kernel based Extreme Learning Machine

Honghui Fan; Wei Xiang*
Department of Plant Engineering, Sichuan College of Architectural Technology, Deyang, 618000, Sichuan, China
* Corresponding author: 313896617@qq.com (W. Xiang)
115569079@qq.com (H. Fan)

Abstract: The dynamic building foundation settlement subsidence are threatening the urban business and residential communities. In the temporal domain, the building foundation settlement often suffers from high level dynamics and needs real-time monitoring. Accurate quantification of the uncertainty of foundation settlement in the near future is essential for the in-advance risk management for buildings. Traditional models for predicting foundation settlement mostly utilizing the point estimates approach which provide a single value that can be close or distant from the actual one. However, such estimation fails to offer the quantification of uncertainties of estimation. The interval prediction, as an alternative, can provide a prediction interval for the ground settlement with high confidence bands. In this paper, a lower upper bound estimation (LUBE) approach integrated with kernel based extreme learning machine (KELM) is proposed to predict the ground settlement levels with prediction intervals in the temporal domain. Comparison with the artificial neural network (ANN) and classical extreme learning machine (ELM) are conducted in this study. Building settlement data collected from Fuxing City, Liaoning Province in China has been used to validate the proposed approach. Comparative results show that the proposed approach can construct higher quality prediction intervals for the future foundation settlement.

Keywords: Foundation settlement; Time-series analysis; Prediction Interval; Kernel based Extreme Learning Machine; LUBE

1 Introduction

Ground settlement is considered as a commonly seen geological phenomenon and it threatens the local communities. The major factor that induces the ground settlement is the soil liquefaction which softened the soil ground and cause buildings settle more than the soil in the free-field. As a consequence, the shear stresses and contact pressure imposed by buildings change due to the soil softening and impact building settlement levels (Karimi et al. 2018; Wei et al., 2020). Nevertheless, the settlement an incremental process and is dynamic in the temporal domain. The future settlement prediction matters to the risk management of the potential building structural damages. Hence, it is necessary to conduct research in predicting foundation settlement in the temporal domain.

In the literature review, soil physics and numerical simulations have been widely discussed for the modeling of ground settlement. Dashti et al. (2010) intensively investigated the mechanism of building foundation settlement and discovered it is heavily depending on the characteristics of the earthquake motion, liquefiable soil, and building. Bullock et al. (2019) developed a physics-based semi-empirical probabilistic model to assess the risk of liquefaction-induced permanent building settlement via 50 case studies. Synthetic Aperture Radar (SAR) sensors via advanced differential interferometric techniques (generically called “DInSAR”) are widely applied to compute the settlement severity according to Petudo et al. (2013). Ng et al. (2015) performed a series of 3D centrifuge model tests to
investigate the ground settlement caused by piggyback twin tunneling. Wang et al. (2019) conducted shake-table tests to analyze the relationship between foundation settlement and the degree of soil liquefaction. Zhang et al. (2020) constructed a 3D fluid-solid coupling finite element model to simulate the ground responses induced by tunneling crossing the interface of water-bearing mixed ground. In general, such approaches can be successfully applied on the case-specific geological conditions. However, the ground subsidence is a complex system with heterogeneous geological and geo-mechanical characteristics. Hence, a more comprehensive approach is needed to model and predict the ground settlement which can be transferred to a variety of cases with heterogeneous conditions.

On the contrary, the machine learning algorithms have demonstrated its effectiveness and accuracy in modeling ground settlement. Santos & Celestino (2008) utilized artificial neural networks in predicting the tunnel-induced settlement with a case study in Sao Paulo subway construction. Gong et al. (2014) conducted site exploration and Monte Carlo Simulation to study the tunnel-induced settlement in clays. Wei & Yang (2018) predicted coal-mining induced ground settlement using online-sequential extreme learning machine (OS-ELM). Moosazadeh et al. (2018) integrated particle swarm optimization (PSO) algorithm and optimized the artificial neural network to predict the building structural damage caused by foundation settlement. Liu et al. (2020) utilized data-mining to select the important predictor variables and predicted the foundation settlement grout holes in the building basement. Recent research has demonstrated that the machine learning algorithms has strong potential to become a comprehensive and reliable approach in studying the building foundation settlement. Nevertheless, all machine learning approaches utilized point-estimation approach which does not sufficiently address the uncertainties in the settlement process that contains huge dynamics. To address this deficiency, the interval-based prediction approach can be a feasible solution.

Among the popular machine learning algorithms, the extreme learning machine (ELM) (Huang et al. 2006) has attracted great attention in the machine learning community in recent years (Ouyang et al. 2020; Li et al. 2017; He et al. 2017a; Xu et al. 2019; Li et al. 2020). The ELM algorithm is a single hidden-layer feedforward network (SLFN) and it produces promising predictive modeling results across various domains in engineering. For instance, Li et al. (2018) integrated LASSO-ELM with parametric Copula models to model and forecast geological landslide displacement in the temporal domain. He et al. (2018) utilized the linear ensemble of multiple ELMs to forecast the wind turbine power generation in the renewable energy sector. Ouyang et al. (2018) developed a data-driven framework to automatically classify the mechanical error codes within the wind turbines. In particular, Wei & Yang (2018) firstly proposed using OS-ELM in predicting coal-mining induced ground subsidence. Cox proportional hazard regression model is utilized to screen the numerical and categorical geological features and OS-ELM is utilized to predict the maximum subsidence by inputting the selected features. The above research using has proved the outperformance in both regression and classification tasks using ELMs.

Based on the discussed outlined above, a data-driven approach using kernel-based extreme learning machine integrated with lower-upper bound estimation is proposed in this study. First, an interval prediction framework is utilized in the building foundation settlement study and a lower upper bound estimation (LUBE) method is adopted. Second, the kernel-based extreme learning machine (KELM) is introduced in this study and the selection of kernels is optimized with cross-validation experiment. Comparative analysis is also performed against the state-of-art approaches such as artificial neural networks and classical extreme learning machine. Through computational results, the proposed approach is feasible and outperforms other building foundation settlement studies.

The main contribution of this paper is as follows:

- First, it proposes an interval prediction framework to estimate the future foundation settlement with quantified uncertainties. A lower-upper bound estimation (LUBE) method is applied in the current research.
- Second, it utilized kernel-based extreme learning machine (KELM) to enhance the predictive performance of future foundation settlement. Comparative analysis across multiple kernels is
conducted to select the optimal kernel for the case studies.

To realize this proposed approach, this paper is organized as follows. Section 2 introduces the data collection process and defines the underlying problem in the mathematical manner. Section 3 provides in the in-detail description of the methodologies utilized in this study. Section 4 studies and compares the models’ performance on geological data collected from the monitoring sites. Finally, Section 5 concludes this study.

2 Foundation Settlement & Problem Formulation

2.1 Foundation Settlement

In Northern China, building foundation settlement is a commonly seen phenomena and has resulted millions of dollars of economic losses and some casualties. The major cause of the foundation settlement can be attributed to the soil liquefaction which changes the shear stress in the foundation soil. It would result deviatoric deformation within the liquefiable soil under the building foundation, as well as volumetric strains due to localized drainage during shaking. As a consequence, the body of the underlying building will be unevenly settled and potentially have large scale building movements for the part above the ground as illustrated in Figure 1.

Figure 1. Schematic diagram of Building Foundation Settlement.

In engineering geology society, engineers would construct physics models to compute and forecast the incoming foundation settlement depending on the effect of gravity of the building above. However, in practice, there always exist a difference between the theoretical settlement and the actual settlement curve. As illustrated in Figure 2, the actual settlement monitoring and forecasting is a post-hoc analysis which can benefit the risk management process of the building structure respectively.
Our case study area is located in Fuxin City, Liaoning Province, China. Many buildings have 20-30 years of age and are located in the urbanized area or suburbs are facing the problem of foundation uneven settlement. In such area, the complex combination of the underground water level change as well as the anthropogenic origin has caused and accelerated the soil liquefaction process and resulted foundation settlement. In recent years, many meter-long cracks have started to emerge on building foundation as well as walls of lower levels. The location of our study area and some example pictures of building foundation settlement has been presented in Figure 3.
2.2 Data collection

The dataset has been collected and provided via collaboration with the engineering geology experts from Liaoning Technical University, School of Geomatics which locates in the case study area. They have spent years monitoring multiple building in down and suburbs in the local area.

The diagram that illustrates the collection of the time-series settlement has been presented in Figure 4. In the four case study buildings, a monitoring point was configured on the edge of the building. The location was set as 4 meters above the ground level as the initial setting. Then, it measures altitude from the ground level on daily basis and take the absolute difference from the previous day’s measurement as the incremental settlement change. For each case study building, they have placed 2 to 3 monitoring points in order to avoid measurement errors from a single point.

The dataset provided contains the daily monitoring foundation settlement from Jan 2013 to April 2013. We select the point with largest cumulative settlement for each case study building. In total of 120 time-series observations are obtained for each building. The basic information of the dataset has been provided in Table 1 which includes the unit, building type, maximum daily settlement, maximum cumulative settlement, mean daily settlement, and the standard deviation of the daily settlement.

| Dataset | Unit | Type   | Max daily settlement | Cumulative settlement | Mean daily settlement | STD daily settlement |
|---------|------|--------|----------------------|-----------------------|----------------------|---------------------|
| Building A | mm/day | Hotel  | 0.043                | 3.235                 | 0.025                | 0.009               |
| Building B | mm/day | Residential | 0.041               | 3.295                 | 0.026                | 0.008               |
| Building C | mm/day | Residential | 0.019               | 1.728                 | 0.014                | 0.010               |
| Building D | mm/day | Commercial | 0.047               | 3.405                 | 0.028                | 0.006               |
2.3 Problem formulation

The main object of this research is to develop a data-driven framework to predict the interval of possible values of foundation settlement in the near future in the temporal domain. For each case study, the foundation settlement is monitored on daily basis and target is to predict the incoming daily settlement value. Hence, the underlying problem can be formulated in (1) as follows:

\[ x_t = f(x_{t-1}, x_{t-2}, ..., x_{t-k}) \]  

where \( x_t \) represents instant settlement in the future at time \( t \); \( x_{t-k} \) denotes the historic lagged settlement based on the actual measurement. Thus, in order to provide the prediction of settlement for a whole period in the future, this research adopted a sequential prediction strategy introduced in Section 3.5 respectively.

3 Methodology

3.1 Auto-correlation Analysis

The daily foundation settlement is a time-series data format in the temporal domain. In many cases, the daily settlement always reflects strong statistical patterns including seasonality and auto-correlation (Zhou et al. 2018). Identification of such patterns is essential to the construction of the time-series prediction models as it determines the optimal input size. Here, two fundamental statistical indexes are adopted to discover the statistical auto-correlation patterns: the auto-correlation function (ACF) and the partial auto-correlation function (PACF).

The ACF measures the Pearson’s correlation coefficient between the current settlement and its \( k \)-lagged historic settlement series. Meanwhile, the PACF computes the additional contribution from the lag-\( k \) series to the current settlement which is non-zero in most of the case. The ACF and PACF are computed via (2) and (3) (Ouyang et al. 2017) as follows:

\[ \rho_k = \frac{\text{Cov}(x_t, x_{t-k})}{\sqrt{\text{Var}(x_t)\text{Var}(x_{t-k})}} \]  

\[ \emptyset_k = \text{corr}(x_t, x_{t-k}|x_t, x_{t-1}, ..., x_{t-k-1}) \]  

where \( x_t \) and \( x_{t-k} \) are the current and \( k \)-lagged settlement series; \( \rho_k \) is the ACF and \( \emptyset_k \) is the PACF which computes the conditional correlation between \( x_t \) and \( x_{t-k} \) respectively.

3.2 Kernel-based Extreme Learning Machine

The Extreme Learning Machine (ELM) (Huang et al. 2006) is a single hidden-layer feedforward neural network (SLFN). Compared with the classical artificial neural networks, it only contains three components: the input layer, the single hidden layer, and the output layer. Given a pair of input/output data sample \((x_i, y_i)\), the classical ELM can be formulated as follows in (4) (Wei et al. 2018):
where $\beta_i$ represents the weight vector connecting the $i^{th}$ hidden neuron and the output neuron. The $h(x_i)$ serves as a general mapping function that maps the input features into the latent space (He et al. 2018). Hence, a compact form of ELM can be written as (5):

$$H\beta = y$$

where $H$ and $\beta$ are expressed as follows:

$$H = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_N) & \cdots & h_L(x_N) \end{bmatrix}$$

$$\beta = [\beta_1, \beta_2, \ldots, \beta_N]$$

To obtain the optimal solution for the ELM, the least-square solution can be computed by (8) as follows:

$$\hat{\beta} = H^\dagger y$$

where $\dagger$ denotes the Moore-Penrose generalized inverse. Figure 5(a) depicts the classical structure of the ELM algorithm.

In addition to the classical ELM, due to the unknown/unspecified feature mapping, we can hardly calculate the Moore-Penrose inverse in (8). Hence, a kernel version of ELM can be obtained by defining a kernel matrix as follows:

$$K = HH^T$$

$$K_{ij} = h(x_i)h(x_j) = k(x_i, x_j)$$

where $K$ is the kernel matrix. The output function of KELM for a new testing observation can be computed by (11) as follows:

$$s = h(\tilde{x})\hat{\beta} = h(\tilde{x})H^T(HH^T)^{-1}y = \begin{bmatrix} k(\tilde{x}, x_1) \\ \vdots \\ k(\tilde{x}, x_N) \end{bmatrix} K^\dagger y$$

In this study, we study the effectiveness of the two popular kernels, i.e., Gaussian kernel (12) and polynomial kernel (13) as follows:

$$k_1(x_i, x_i) = \exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right)$$

$$k_2(x_i, x_i) = (\varphi(x_i) \cdot \varphi(x_j))^2$$
\[ k_2(x_i, x_j) = (x_i^T x_j)^d \]  

(13)

where \( \sigma \) is the kernel width and \( d \) denote the polynomial degree respectively. An explicit interpretation of the impact regarding the kernel function is presented in Figure 5(b) respectively.

\[ \sigma \] is the kernel width and \( d \) denote the polynomial degree respectively. An explicit interpretation of the impact regarding the kernel function is presented in Figure 5(b) respectively.

**3.3 Prediction Interval Formulation with LUBE Method**

Prediction intervals (PIs) are widely used for the quantification of uncertainty in the prediction models. Given an input feature vector \( x_i \), the PI with confidence level \( 100(1-\alpha)\% \) constructed for the prediction target \( y_i \) can be expressed in (14) as follows:

\[ I^{(\alpha)}(x_i) = [L^{(\alpha)}(x_i), U^{(\alpha)}(x_i)] \]

(14)

where \( \alpha \) denotes the quantile of the standard normal distribution; and \( L^{(\alpha)}(x_i) \) and \( U^{(\alpha)}(x_i) \) are the lower and upper bounds of the \( i \)th PI as illustrated in Figure 5(a). The prediction target settlement is expected to be covered by \( I^{(\alpha)}(x_i) \) with a coverage probability given by the following equation expressed in (15):

\[ P(L^{(\alpha)}(x_i) \leq y_i \leq U^{(\alpha)}(x_i)) = 100(1 - \alpha)\% \]

(15)
In this study, the lower upper bound estimation (LUBE) method is adopted to customize the KELM model as presented in Section 3.2. The PIs are constructed as outputs for the KELM algorithm. As indicated in Figure X, the proposed KELM contains two output neurons. The upper and power bound can be formulated in (16-17) as follows:

\[
\hat{U}(\alpha)(x_i) = \max\{o_{j1}, o_{j2}\} \\
\hat{L}(\alpha)(x_i) = \min\{o_{j1}, o_{j2}\}
\]

where \(x_i\) denotes the \(j^{th}\) input; and \(o_{j1}\) and \(o_{j2}\) are the lower and upper outputs for the \(j^{th}\) input sample as indicated in Figure 6 respectively.

### 3.4 Training and Testing Strategies

In this research, the historic lagged settlement values are selected as inputs and the future settlement value is the output. From the four case studies, we collected in total of 120 settlement observations from Jan 2013 to April 2013 for each settlement case. The 90 observations between January and March in 2013 are used as training/validation set and the remaining 30 observations in April 2013 are regarded as testing dataset.

In order to predict the settlement, a sequential prediction strategy is adopted in research to predict the periodic foundation settlement as described in Figure 6.

Figure 6. Sequential prediction strategy.

According to Figure 6, the inputs and outputs are defined in the time-series prediction model. The \(k\) historic values of the settlement are used as inputs in the prediction model. The optimal value of the \(k\) is determined via the
auto-correlation analysis considering the ACFs and PACFs computed. Meanwhile, the single settlement at time $t$ is the output of the prediction model. In order to predict the settlement at time $t+1$, the predicted settlement at time $t$ and its $k$-lagged historic settlement values are selected as the new inputs. The output is the settlement at time $t+1$. After training it repeatedly in a sequential manner, the periodic incoming settlement can be predicted and compared with the ground-truth for model evaluation purposes.

### 3.5 Prediction Performance Measure

In this research, two widely utilized metrics namely prediction interval coverage probability (PICP) and prediction interval normalized average width (PINAW) (Ouyang et al. 2019) are selected in this study to measure the performance of prediction intervals. The PICP and PINAW can be computed according to (18-19) as follows:

$$\text{PICP} = \frac{\sum_{i=1}^{N} c_i}{N}$$  \hspace{1cm} (18)

$$\text{PINAW} = \frac{\sum_{i=1}^{N} [\hat{L}^{(\alpha)}(x_i), \hat{U}^{(\alpha)}(x_i)]}{y_{\max} - y_{\min}}$$  \hspace{1cm} (19)

where $N$ represents the number of observations; $y_{\max}$ and $y_{\min}$ are the minimum and maximum values of the true target. The variable $c_i$ is a binary indicator function determining whether the target falls into the limit of PI which can be expressed in (20) as follows:

$$c_i = \begin{cases} 1 & y_i \in [\hat{L}^{(\alpha)}(x_i), \hat{U}^{(\alpha)}(x_i)] \\ 0 & y_i \notin [\hat{L}^{(\alpha)}(x_i), \hat{U}^{(\alpha)}(x_i)] \end{cases}$$  \hspace{1cm} (20)

In general, the PICP evaluates the probability that the prediction target falls within the bound between the upper and lower limits. The value of PICP ranges between 0 and 1. The PINAW denotes the mean width of PIs. In most cases, the high value of PICP and the low values of PINAW indicate high-quality PIs (Sun et al. 2017).

### 3.6 Benchmarking Methods

In this research, the artificial neural networks (ANNs) and the classical extreme learning machine (ELM) are selected as benchmarking algorithms for comparative analysis purpose. The classical ELM has been described in detail in section 3.2 of which the only difference compared with the KELM is the kernel function utilized for feature mapping.

Besides, the ANN is a non-parametric algorithm developed based on the processes of learning in the cognitive system and capable of accurately predicting patterns that are not part of the training dataset. The structure of the ANN algorithm ensures its promising performance to construct accuracy mapping between the input and output in a highly non-linear system (He et al. 2017b).

The most essential element that functions within an ANN is the neuron. With multiple neurons stacked in the hidden layers, a non-linear mapping between the input features and the output can be expressed as (21):
\[ y = \varphi(\sum_{i=1}^{n} w_i x_i + b) \]  \hspace{1cm} (21)

where \( x_i \) represents the \( j \)th input feature; \( w_j \) is the weight associated with the \( j \)th input; \( b \) is the bias and \( \varphi \) is the activation function. In this paper, the ANN is also customized with the LUBE method and the sigmoid activation function is utilized respectively.

4 Experimental Results

4.1 Auto-correlation Analysis

Selection of the optimal input feature set matters to the performance of the data-driven models. Inspired by the ARIMA model, the ACF and PACF are computed between the current settlement and its \( k \)-lagged historic settlement to investigate the auto-correlation and seasonality within the dataset. The combination of the ACF and PACF results determines in the final input feature sets.

As illustrated in Figure 7, the ACFs and PACFs are computed for the four time-series datasets for the four cases study building listed in Table 1. The Ljung-Box test statistic is applied to measure the statistical significance of the correlation coefficients. According to Figure 7, the blue lines serves as the threshold of the Ljung-Box test stat and any lagged series with coefficient outside of the band region are considered significant and thus impact the current settlement statistically.
Based on the computational results of ACFs and PACFs, the optimal number of lagged series that can be selected as inputs for the time-series model for building A’s settlement data is 13. For Building B & C, the optimal numbers of lagged series are 7 and 19. In addition, for Building D, the amount of lagged series selected as inputs is 16 respectively.

4.2 Hyper-parameter Optimization

After the selection of optimal input series, three algorithms including artificial neural network algorithm (ANN), classical extreme learning machine (ELM) and kernel extreme learning machine (KELM) are selected for training and validating the time-series prediction model. To ensure the models can achieve the optimal prediction performance, tuning the hyperparameters is an essential component in the process.

In Table 2, the number of hyper-parameters for the three algorithms as well as the various initial settings for the parameters are presented. For the ANN algorithm, there are two hyperparameters that need optimization: the number of hidden layers and the number of hidden neurons in each layer. For the classical ELM algorithm, the number of hidden neurons within the hidden layer is the only hyperparameter that need to be optimized. For the KELM, its
hyperparameters include the number of hidden neurons in the hidden layer and the selection of kernel functions for feature mapping. The PICP is selected as the measurement metric for the selection of optimal hyperparameter settings regarding the three algorithms listed above.

Table 2. List of hyperparameters tested for ANN, ELM and KELM

| Algorithm | Hyperparameter Settings |
|-----------|------------------------|
| ANN       | Hidden layer = 1, 2, 3, 4, 5  
|           | Hidden neuron = 5, 10, 15, 20, 25, 30, 35, 40 |
| ELM       | Hidden neuron = 5, 10, 15, 20, 25, 30, 35, 40 |
| KELM      | Kernel = Gaussian, Polynomial  
|           | Hidden neuron = 5, 10, 15, 20, 25, 30, 35, 40 |

According to computational results, the ANN algorithm with 2 hidden layers and 10 hidden neurons in each layer has the smallest PICP value. For the classical ELM, the optimal number of hidden neurons is 15. For the KELM algorithm, the best performing kernel function is the Gaussian kernel and the optimal number of hidden neurons is 15 also. The training and validation of the optimal setting of the KELM tested on the four cases study building settlement time-series data is presented in Figure 8 accordingly.

![Figure 8](image_url)

(a) Building A  
(b) Building B  
(c) Building C  
(d) Building D

According to computational results, the ANN algorithm with 2 hidden layers and 10 hidden neurons in each layer has the smallest PICP value. For the classical ELM, the optimal number of hidden neurons is 15. For the KELM algorithm, the best performing kernel function is the Gaussian kernel and the optimal number of hidden neurons is 15 also. The training and validation of the optimal setting of the KELM tested on the four cases study building settlement time-series data is presented in Figure 8 accordingly.

4.3 Foundation Settlement Prediction

Based on the obtained optimal settings for the hyperparameters, the prediction of the testing data for the four
time-series settlements in the month of April 2013 are performed. In this research, the prediction of the testing dataset are hidden in blind and we adopted the sequential prediction strategy as illustrated in Figure 6 to predict the daily incremental settlement for the four buildings. Then, the prediction intervals are overlaid with actual measured incremental settlement as shown in Figure 9 as follows.

![Figure 9. Prediction intervals constructed for the testing dataset using KELM.](image)

As illustrated in Figure 9, there exist prediction errors between the actual measured settlement and the predicted settlement. If we consider the systematic uncertainty in the prediction process, prediction intervals (PIs) can be constructed and the majority of the actual settlements falls within the 95%-confidence level PIs according to the prediction outcome. However, as there still exist few outliers which falls outside of the PIs and hence, we use the overall measurement metrics (i.e., PICP and PINAW) to computed the overall prediction performance as presented in Table 3.

| Algorithm | Building A | Building B | Building C | Building D |
|-----------|------------|------------|------------|------------|
|           | PICP | PINAW | PICP | PINAW | PICP | PINAW | PICP | PINAW |
| ANN       | 76.7% | 50.1% | 86.7% | 27.7% | 73.3% | 26.7% | 93.3% | 25.1% |
| ELM       | 80.0% | 49.7% | 90.0% | 30.8% | 83.3% | 30.3% | 100.0% | 25.6% |
| KELM      | **86.7%** | **27.9%** | **90.0%** | **21.5%** | **93.3%** | **19.2%** | **100.0%** | **24.9%** |

According to Table 3, the PICP of the KELM integrated with the LUBE method are computed for ANN, ELM, and KELM. For the four buildings settlement time-series, the KELM outperforms among all algorithms tested and
produces the highest mean PICPs and lowest mean PINAWs. Based on the intrinsic formulation of these two metrics, the higher values of PICP and lower values of PINAW indicate more accurate and reliable of interval prediction results. Hence, the effectiveness and robustness of the prediction power of the KELM with respect to the interval prediction is demonstrated.

5 Conclusion

For predicting building foundation settlement, a novel data-driven framework for interval prediction of time-series settlement prediction is presented in this study. First, the lower-upper bound estimation approach is applied to construct the prediction intervals. Second, a kernel-based extreme learning machine is customized for the interval prediction task and predicts the future settlement. Third, time-series analysis is performed to investigate the autocorrelation between the current measured settlement and its historic series. Four case studies in Liaoning Province have been selected in this study and the daily settlement is monitored in the temporal domain. Computational results validate the superiority of the proposed algorithm via comparison with the benchmarking methods including ARIMA and classical ELM. Therefore, it’s feasible to utilize this approach to monitor and assess the building structural risk in the near future.

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