Author/s:
Yousefpour, N;Medina-Cetina, Z;Briaud, JL

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EVALUATION OF UNKNOWN FOUNDATIONS OF BRIDGES SUBJECTED TO SCOUR USING ARTIFICIAL NEURAL NETWORKS

ABSTRACT

The missing substructure information has impeded the safety assessment for bridges with unknown foundations especially for scour-prone bridges. An Artificial Neural Network (ANN)-based approach was developed to identify the inherent patterns in the design of substructure of bridges with commonly available evidence (e.g. geometric characteristics of superstructures, loading conditions, soil properties, year built, and location of bridges), and then further generalize them to bridges with unknown foundations. The proposed ANN models were trained using information collected for an inventory of bridges with available foundation records located within the Bryan District of the Texas Department of Transportation. Results showed that the proposed ANN models were able to make successful predictions about the foundation type and the embedment depth for deep foundations. In addition, by performing the random subsampling method the degree of uncertainty in the models' predictions was evaluated. Also, Probability of Exceedance graphs were generated that allowed for factoring the predicted pile depth based on a reasonable probability of failure due to scour. As a consequence, it is anticipated that DOTs can adopt a similar methodology to reclassify the bridges with unknown foundations included in the National Bridge Inventory.

Keywords: Unknown Foundations, Pile Embedment Depth, Artificial Neural Networks, Bridge Scour, Random Subsampling.

INTRODUCTION

As of 2005, approximately 60,000 bridges throughout the United States were identified as having unknown foundations. Texas alone accounted for 9,113 of them, being the largest population of Unknown Foundation Bridges (UFBs). The major concern of FHWA and DOTs regarding UFBs focuses on the risk of failure due to scour at bridge interior piers, as scour is the primary cause of failure for 60% of all the bridge in the country (*1*), and accounts for 95% of severely damaged and failed highway bridges constructed over waterways in the United States (*2*). Thus, for these bridges predicting the embedment depth is critical for evaluating the safety state of the bridges against scour failure.

There are a number of studies on applying nondestructive testing (NDT) to obtain information about UFBs (*3*-*8*), while only very few studies have used statistical, computational, and/or numerical solutions to infer foundation characteristics. Risk-based approaches have been implemented by the National Cooperative Highway Research Program (NCHRP) and Florida DOT to manage bridges with unknown foundations susceptible to scour (*9*-*11*). Florida DOT approach to reclassify the UFBs included locating design and construction plans, risk-based evaluation based on the NCHRP, ANNs, reverse engineering, and NDT methods. Also, a back-calculation (reverse engineering) method was developed by (*12; 13*), based on the static equilibrium of a bridge, to reclassify unknown foundations by predicting a conservative minimum embedment depth. Soft computing techniques in general, and ANNs in particular, have recently accommodated the safety assessment and management of transportation infrastructure, including bridge safety and structural integrity assessment (*14*-*18*). ANNs have been widely used to infer scour depth at bridge piers (*19*-*22*). Florida DOT developed an ANN model (CPILE) to predict the pile embedment depth (applicable only for concrete piles) based on a number of input variables including pile size, pile design load, slope of the bearing capacity curve, and construction year (*11*). Also, some studies have explored the use of ANNs to interpret the results of NDTs for evaluation of UFBs (*23*). A more recent study explored the use of Electrical Resistivity Imaging (ERI) and Induced Polarization (IP) to infer the characteristics of unknown foundations (*24; 25*).

This study provides a guideline and methodology for predicting the type and embedment depth of unknown foundations of bridges in order to facilitate the evaluation of the scour vulnerability for these bridges. An evidence-based approach was developed based on a database of bridges located in Bryan District of TxDOT. The proposed method applied ANNs to identify the inherent patterns in the substructure characteristics of the bridges with commonly available evidence (e.g. geometric characteristics of superstructures, loading conditions, soil properties, year built, and location of bridges), and then to further generalize them to UFBs.

APPROACH

Database and Statistics

A sufficient dataset was populated including approximately 40% (about 185) of the on-system bridges (with known foundations) built over waterways. These bridges were sampled from four populations of bridges with major foundation types including concrete piling (**Conc**), drilled shafts (**DrSh**), steel piling (**Steel**), and spread footing (**Spread**) according to their actual distribution throughout the Bryan District (54, 22, 12, 4%) respectively. It was observed that very few of over-waterway bridges had spread footings. Figure 1 shows the location of the bridges in the Bryan District of the TxDOT included in this study, along with the Item 113, Scour-Critical index of bridges in the National Bridge Inventory (NBI), and year built. This map indicates the location of the most and least scour-critical bridges. For each of the bridge's interior bents, the relevant data for a representative pile of that bent was collected. Relevant information for inferring the type and embedment depth of each foundation was identified based on the design procedures specified by AASHTO and TxDOT standards (*26*). This set of data was collected from the inspection folders and TxDOT bridge inventory and inspection database. Some data including the dimensions and embedment depth of foundations was directly extracted from the design and construction plans found in the bridge inspection folders. Also, soil boring data found in the bridge inspection folders provided the type and strength of soil based on the results of *in-situ* soil tests using the Texas Cone Penetrometer (TCP). The ultimate skin friction (f_u) along the piles was computed from the *TCP* values using the correlation graphs defined by the TxDOT (*26*). Table 1 presents the main items in the database. Some of these items were used for pile embedment depth estimation and some for foundation type prediction, as will be described in the following sections.

Guideline and Methodology

Figure 2 presents the guideline flowchart for the proposed method, which includes the following steps:

Step 1: Data Collection. Acquire the required parameters for a bridge interior bent (pier), as listed below. These items can be found in the NBI and in the inspection folders of the bridge. Further details on the description of each item can be found in the TxDOT's coding guide (*27*):

- Item 3: County
- Item 16: Latitude
- Item 17: Longitude
- Item 27: Year built
- Item 31: Design load
- Item 34: Bridge Skew
- Item 44.1-D1: Substructure type above ground for main spans
- Item 46: Total number of spans in bridge
- Item 48: Max span length
- Item 51: Roadway width
- Average TCP and skin friction along the piles (from soil boring data, if available)
- Average span length for the bent (from bridge inspection documents)

Step 2: Determining the Foundation Type Using ANNs. The type of foundation is predicted using two ANN classifier models. The ANN models were trained with a number of bridge examples to learn the existing pattern in the relation between bridge input parameters and the foundation type. One of the proposed ANN classifiers can be used to predict any of the eight common foundation types (steel, concrete, timber piling, drilled shafts, spread footing, and pile cap on timber, concrete and steel piling), whereas the other one can solely distinguish between deep and shallow foundations. If the foundation is shallow (spread footing), then it is recommended to implement the Bayesian probabilistic method developed by the authors to evaluate the dimensions and embedment depth of the foundation, or to use an NDT method (*24*). Nevertheless, a shallow foundation is normally considered to be highly susceptible to scour failure. If the foundation is deep then one can proceed to estimate the embedment depth.

Step 3: Determining the Depth of the Hard Layer. If soil boring data is available for the foundation or another adequately close foundation, then it is recommended to identify whether a hard layer (such as rock or shale) exists in the soil profile, and then estimate the depth of that hard layer. Based on the TxDOT Geotechnical Manual (*26*), drilled shafts should penetrate into a hard layer at least for one shaft diameter if that hard layer is more than three shaft diameters below the surface. Otherwise, if the hard layer is close to the surface, shafts are recommended to have a minimum length of three shaft diameters into the hard layer. However, pile driving is normally stopped upon refusal when reaching a layer with TCP >100 (blows/ft) (*26*). The plans for over-river bridges in the Bryan District's database also showed that driven piles and drilled shafts were mainly extended up to the hard layer.

Step 4: Calculating Dead Load and Live Load. A simple, fast method is proposed in this study to estimate with reasonable accuracy, the dead loads and live loads for bridge foundations. This procedure was designed based on the standard bridge design sheets used by TxDOT (*24*). The total load for a bridge bent is estimated using the standard tables depending on roadway width and span length. The live load is calculated based on the standard design vehicles specified by the AASHTO-LRFD, which is given by Item 31 of the NBI for a bridge. The dead load is then calculated by subtracting the live load from the total load. Figure 3 presents the steps of the total load calculation procedure. The method is explained in full detail in (*24; 28*).

Step 5: Obtaining Foundation Properties. Obtain the above-ground properties of the bridge's substructure such as the dimension and number of piles/shafts in the bent.

Step 6: Predicting Pile Depth Using ANN Models. Depending on the availability of soil boring data and foundation type information available, four scenarios are defined in the following sub-steps:

Step 6-1: If the foundation type is known to be deep but neither the foundation type nor the soil data are available, the ANN model called **MLP-PL00** is recommended for predicting the foundation depth. This scenario assumes that the user is only interested in inferring the foundation's depth.

Step 6-2: This step addresses a scenario in which the foundation type is known to be deep, the exact foundation type is unknown, but the soil data is available.

Step 6-2-1: Compute the average *TCP* value and the ultimate skin friction (f_u) based on the *TCP* values along the piles from the nearest soil boring data and using the TxDOT design graphs, as previously explained.

Step 6-2-2: Implement the ANN model **MLP-PL01** to predict the pile embedment depth.

Step 6-3: This step addresses a scenario in which the foundation type is either known or is determined using the ANN classifier, and the soil boring data is available.

Step 6-3-1: Compute the average *TCP* value and skin friction (f_u) along the piles.

Step 6-3-2: Implement **MLP-PL11** to predict pile embedment depth.

Step 6-4: If the foundation type is known but the soil boring data is not available, then implement the ANN model **MLP-PL10** to infer the embedment depth of the piles.

The minimum value between the depth of the hard layer and the predicted pile depth by the ANN model is considered to be the pile depth.

Artificial Neural Networks

Artificial Neural Networks (ANNs) have been successfully applied to regression, prediction, and classification problems. In particular, ANNs have been implemented successfully for various function approximation and regression problems in civil and geotechnical engineering (*29*). Different ANN types and architectures were formulated in this study to predict both the foundation type and the embedment depth, including Radial Basis Function (RBF), Multi-Layer Perceptron (MLP), Probabilistic Neural Network (PNN), and Generalized Regression Neural Network (GRNN). The architecture and learning algorithms for different types of ANNs are fully described in (*30; 31*). A preliminary analysis was performed to find the best network type using a fraction of the database. Results of this study showed that MLP with Levenberg-Marquardt (LM) algorithm significantly outperformed RBF and GRNN for pile depth prediction, and PNN in foundation classification (*24; 28; 32*).

For the purpose of training, the working database was split into three groups: training, validation, and test with 3:1:1 proportions. In order to make a reasonable estimate of the performance of the models (error), the Random Subsampling method (Monte-Carlo Cross Validation) was implemented (*33*). As a result of this method, ensembles of networks were generated that could work in parallel to make predictions. The training time to generate an ensemble of networks (1000 retraining times) was in the order of hours to a couple of days, and evaluating the ensemble of networks to make a prediction about a bridge foundation was in the order of a few seconds to a few minutes. The average of the predictions over all networks in an ensemble was considered as the best estimation. In this study, the ANN networks in an ensemble with R^2 (Test) < 0.7 were removed, which resulted in an ensemble of best networks to be used as a predictive model.

Foundation Type Prediction

ANN classifiers are powerful tools for classifying categorical data. In this study, the classifier performance was measured by the classification accuracy (CA), which was defined as the ratio of the correctly classified examples over the total number of examples. Identifying the foundation type is essential for determining the foundation embedment depth and scour vulnerability. The selected input parameters for the ANN classifiers are factors that can influence the decision making process for selecting the type of a foundation at the time of design. A stepwise parameter selection method (forward and backward selection) was implemented to select the most relevant parameters that contributed to the foundation type classification (*34*). The target parameter is the foundation type (class), which was found in the Item 44-1-D2 (defined as the substructure type below ground) for the bridges in the database. Figure 4 shows the architecture of the MLP classifier and the input parameters used to predict the foundation type.

Foundation Embedment Depth Prediction

The criteria for selecting the relevant input parameters for pile depth prediction was based on the limit state design method of foundations, which required the foundation load and the allowable bearing capacity to be equal. These parameters associated with the superstructure, substructure, load, year built, and location of the bridge. Several networks with different combinations of these parameters were created and compared to determine the most relevant input parameters. The list of the input parameters and the architecture of the MLP network used for pile depth prediction are presented in Figure 5. Note that depending on the bridge design and construction practice in a district, the relevant input parameters for the ANN models can change. For instance, for a district with SPT as the prevailing soil testing method, Ave. TCP parameter can be replaced by SPT.

RESULTS AND DISCUSSION

Foundation Type Prediction

Figure 6 presents the classifications among eight possible foundation types (FT8) and the classifications between deep and shallow foundations (FT2) for the bridge records in the database. The plots of predicted versus actual foundation types were generated by one of the networks in the MLPFT8 and MLPFT2 ensembles. Table 2 presents the average of the *CA* for the full and reduced MLPFT8 and MLPFT2 ensembles. From this table, it can be observed that both MLP-FT8 and MLP-FT2 were able to classify the foundations with a good level of accuracy. The average *CAs* over the test subsets for MLP-FT2 and MLP-FT8 were 0.90 and 0.75, respectively. Thus, it was significantly more accurate to classify a foundation as deep or shallow rather than to identify the exact foundation type. Comparing the performance of the full and reduced MLP models, it can be observed that the proposed parameter selection method improved the prediction accuracy particularly for MLP-FT8.

Foundation Depth Prediction

Eight different MLP models were developed to predict pile depth based on the availability of soil data and the foundation type. These models are **MLPPL00** and **MLPPL01**, as well as **MLPPL10** and **MLPPL11** developed for each of the three foundation types i.e. **Conc**, **DrSh**, and **Steel**. Note that for the scenarios assuming that the soil data 'is not available', the soil strength parameters were eliminated from the list of input parameters, leaving seven input parameters to be used. For the scenarios assuming that the soil data 'is available', all the nine input parameters were used to train the models. Figure 7 shows the average over the pile depth values predicted by the networks in each MLP ensemble. The data points in each graph represent the average predicted pile depth versus the measured pile depth for all the bridge pier records in the corresponding databases. This figure shows only the average predictions over all the networks in the ensembles. R^2 and *RMSE* for the average ensemble predictions are also presented in this figure. The performances of the models can be compared through the R^2 of the average predictions. After comparing **MLPPL00** with **MLPPL01** and **MLPPL10** with **MLPPL11**, it was observed that adding the soil strength parameters as inputs to the model significantly improved the models' performances. It can be observed that for all eight MLP models, except for steel piling, the order of magnitude of R^2 of the average predictions for the examples in the working data set was 0.8 or above. This indicates that these models were able to assimilate the proper information from the examples in the training set and then predict new cases with reasonable accuracy. Due to the limited amount of data for steel piling, the **Steel** models could not generate predictions as accurate as the two other types of piling.

Figure 8 shows the predicted versus actual pile depth generated by the **MLPPL00** ensemble, which includes the predicted values by all the networks in the ensemble. It also presents the average of the ensemble predictions along with the 95% prediction intervals and the 10th percentiles of the predicted pile depth distributions. The 10th percentile threshold provides a conservative estimation of the pile embedment depth with only 10% of the predicted pile depth values smaller than that. In addition, this figure presents the Probability of Exceedance (PoE) curve developed from the predicted pile depths by **MLPPL00** networks versus the actual pile depths. Similar plots were generated for all the eight MLP models (*28*). The horizontal axis in the PoE graphs corresponds to a correction factor *C* that was multiplied by the predicted values of the pile depths:

$$d_p(corrected) = Cd_p(predicted)$$
$$PoE = \Pr(d_p(corrected) > d_p(actual)) = \frac{N_{above}}{N_{total}} \quad (2)$$

where d_p is the pile depth, N_{above} is the number of data points above the equality line in the scatter plot of $d_p(corrected)$ versus $d_p\ (actual)$ values, and N_{total} is the total number of data points.

If $d_p(corrected)$ is larger than $d_p(actual)$, the foundation depth (and therefore the allowable scour depth) is overestimated, which could result in the foundation failure. Thus, the goal is to minimize the value of *PoE* for a prudent design by selecting a reasonable value for *C*. A target value of 10^{-3} for *PoE* is suggested, as it is a probability of failure consistent with other areas of engineering and everyday life (*35*). The generated PoE graphs allow for adjusting the pile depths predicted by the MLP models (by multiplying with a factor *C)* for an acceptable probability of failure, where failure is over predicting the pile depth.

Case Study

In order to further validate the proposed methodology for an actual UFB, a case study has been performed for the bridge 17-021-0116-04-046 on the west bound state highway 21 over the Little Brazos River. The bridge construction plan for the west bound was not available and the bridge was assumed to have unknown foundation. The construction plans for the other bridge (17-021-0116-04-052) on the east bound of this highway were collected. This bridge was founded on three drilled shafts of 36 in (0.9 m) diameter with 34 ft (10.4 m) embedment depth for the pier over river. The information of this bridge served as a guide to the characteristics of the unknown foundation for the west bound bridge. The west bound bridge was visually inspected and an electrical resistivity imaging (ERI) experimentation was performed at the pier over the rive by Arjwech et.al (*24; 25*). The ERI profile at the bridge pier and the resulted image are presented in Figure 10. The inversion results show low resistivity anomaly (~2-3 Ωm) at the location of the foundation to depths > 5 m.

The relevant input information was found from the inspection database for this bridge as listed in Table 3. The dead load and live load were computed based on the proposed procedure. The soil boring data at the east bound bridge were used to compute soil properties (No hard layer existed near the surface). Using MLPFT2 the foundation was predicted to be deep and according to site investigation the substructure above ground includes three drilled shafts with 36 in (0.9 m) diameter. The four proposed ANN models were implemented to identify the embedment depth of the drilled shafts and the prediction results are presented in Table 3. The estimated embedment depths closely match with the actual embedment depth for drilled shafts in the east bound bridge. Also the estimates are in agreement with the results of the ERI *in-situ* experiment.

CONCLUSIONS

The ANN-Based approach proposed in this study allows DOTs to make predictions about the substructure type and embedment depth of unknown foundations with a reasonable level of accuracy. Using this method, DOTs can reclassify their UFBs and also identify the most critical bridges in terms of scour vulnerability. NDT methods can be performed to supplement and verify the ANN model predictions and characterize the substructure with higher confidence. Based on the initial estimations generated by the ANN models, DOTs can save on their budget by limiting the costly NDT methods to more critical bridges.

The ANN models developed in this study can make reliable predictions only for bridges within the same statistical population (Bryan District). Nevertheless, the proposed methodology can be applied to make predictions for a bridge with unknown foundation in any other district, as long as the models are trained using the evidence from the foundation characteristics for bridges in that District. Implementing the proposed methodology for an adequate number of UFBs in different states can supplement this research. This is conditioned on comparing the results with the exact foundation characteristics obtained by reliable in-situ tests.

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[1] Deng, L., and C. Cai. Bridge Scour: Prediction, Modeling, Monitoring, and Countermeasures—Review. *Practice Periodical on Structural Design and Construction*, Vol. 15, No. 2, 2009, pp. 125-134.
[2] NCHRP Report 396, Instrumentation for measuring scour at bridge piers and abutments.In, Transportation Research Board, 1997.
[3] Mercado, E. J., and M. W. O'Neil. Methods to Measure Scour Depth and the Depth of Unknown Foundations. Presented at 3rd International Conferences on Applied Geophysics, Orlando, 2003.
[4] Olson, L., F. Jalinoos, and M. F. Aouad. *Determination of Unknown Subsurface Bridge Foundations: NCHRP 21-5 Interim Report Summary*, Federal Highway Administration, 1998.

[5] Olson, L. *Dynamic Bridge Substructure Evaluation and Monitoring.* Publication FHWA-DR-03-089, 2005.
[6] Robinson, B., and S. Webster. Successful Testing Methods for Unknown Bridge Foundations. Presented at Fifth Highway Geophysics - NDE Conference, Charlotte, 2008.
[7] Hertlein, B. H., and W. H. Walton. Assessment and reuse of old foundations. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1736, No. 1, 2000, pp. 48-52.
[8] Sack, D. A., S. H. Slaughter, and L. D. Olson. Combined measurement of unknown foundation depths and soil properties with nondestructive evaluation methods. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1868, No. 1, 2004, pp. 76-80.
[9] Pearson, D. R., J. S. Jones, and S. M. Stein. Risk-based design of Bridge scour countermeasures. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1696, No. 1, 2000, pp. 229-235.
[10] Stein, S., and K. Sedmera. Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations.In, National Cooperative Highway Research Program (NCHRP), Springfield,VA, 2006. pp. Project 24-25.
[11] Mclemore, S., S. Zendegui, J. Whites, M. Sheppard, M. Gosselin, H. Demir, P. Passe, and M. Hayden. Unknown Foundation Bridges Pilot Study.In, Federal Highway Administration & Florida Department of Transportation, 2010.
[12] Sayed, S., H. Sunna, and P. Moore. Rational Alternative to Positive Discovery of Pile-Supported Bridges with Unknown Foundation Depth. *Journal of Bridge Engineering*, Vol. 17, No. 1, 2012, pp. 173-181.
[13] Sayed, S. M., H. Sunna, and P. R. Moore. Re-Classifying Bridges with Unknown Foundations. Presented at 5th international conference on scour and erosion, San-Francisco, CA, 2011.
[14] Arangio, S., and F. Bontempi. Soft Computing Based Multilevel Strategy for Bridge Integrity Monitoring. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 25, No. 5, 2010, pp. 348-362.
[15] Elkordy, M. F., K. C. Chang, and G. C. Lee. A Structural Damage Neural Network Monitoring System. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 9, No. 2, 1994, pp. 83-96.
[16] Kawamura, K., A. Miyamoto, D. M. Frangopol, and R. Kimura. Performance evaluation of concrete slabs of existing bridges using neural networks. *Engineering Structures*, Vol. 25, No. 12, 2003, pp. 1455-1477.
[17] Kim, S.-H., C. Yoon, and B.-J. Kim. Structural Monitoring System Based on Sensitivity Analysis and a Neural Network. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 15, No. 4, 2000, pp. 189-195.
[18] Singh, D., M. Zaman, and L. White. Neural Network Modeling of 85th Percentile Speed for Two-Lane Rural Highways. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2301, No. 1, 2012, pp. 17-27.
[19] Zounemat-Kermani, M., A. A. Beheshti, B. Ataie-Ashtiani, and S. R. Sabbagh-Yazdi. Estimation of current-induced scour depth around pile groups using neural network and adaptive neuro-fuzzy inference system. *Applied Soft Computing*, Vol. 9, No. 2, 2009, pp. 746-755.
[20] Kaya, A. Artificial neural network study of observed pattern of scour depth around bridge piers. *Computers and Geotechnics*, Vol. 37, No. 3, 2010, pp. 413-418.
[21] Lee, T. L., D. S. Jeng, G. H. Zhang, and J. H. Hong. Neural network modeling for estimation of scour depth around bridge piers. *Journal of Hydrodynamics, Ser. B*, Vol. 19, No. 3, 2007, pp. 378-386.
[22] Bateni, S. M., S. M. Borghei, and D. S. Jeng. Neural network and neuro-fuzzy assessments for scour depth around bridge piers. *Engineering Applications of Artificial Intelligence*, Vol. 20, No. 3, 2007, pp. 401-414.
[23] Rix, G. J. Interpretation of NondestructiveTests on Unknown Bridge Foundations using Artificial Neural Networks. *Nondestructive Evaluation of Aging Structures and Dams*, Vol. 2457, 1995, pp. 102-112.
[24] Briaud, J.-L., Z. Medina-Cetina, S. Hurlebaus, M. Everett, S. Tucker, N. Yousefpour, and R. Arjwech. Unknown Foundation Determination for Scour.In, Report No. FHWA/TX-12/0-6604-1,Texas Department of Transportation and Federal Highway Adminstration, 2011.

[25] Arjwech, R., M. Everett, J.-L. Briaud, S. Hurlebaus, Z. Medina-Cetina, S. Tucker, and N. Yousefpour. Electrical Resistivity Imaging of Unknown Bridge Foundations. *Near Surface Geophysics*, Vol. 11, No. 6, 2013, pp. 591-598.
[26] TxDOT. Geotechnical Manual.In, Texas Department of Transportaion (TxDOT), 2006.
[27] *TxDOT Coding Guide For Bridge Inventory, Inspection, and Appraisal Files, http://onlinemanuals.txdot.gov/txdotmanuals/ins/coding_guide.pdf*.
[28] Yousefpour, N. Comparative Deterministic and Probabilistic Modeling in Geotechnics: Applications to Stabilization of Organic Soils, Determination of Unknown Foundations for Bridge Scour, and One-Dimensional Diffusion Processes.In *Zachry Department of Civil Engineering, No. Ph.D.*, Texas A&M University, College Station, Texas, 2013.
[29] Shahin, M., & Jaksa, M. State of the Art of Artificial Neural Networks in Geotechnical Engineering. *Electronic Journal of Geotechnical Engineering*, Vol. 8, 2008, pp. 1-26.
[30] Bishop, C. M. *Neural networks for pattern recognition*. Clarendon Press, Oxford University Press, Oxford, New York, 1995.
[31] Haykin, S. *Neural Networks: A Comprehensive Foundation*. Prentice hall International, Inc., 1999.
[32] Yousefpour, N., Z. Medina-Cetina, K. Jahedkar, J. Delphia, J. Briaud, S. Hurlebaus, S. Tucker, M. Everett, and R. Arjwech. Determination of Unknown Foundation of Bridges for Scour Evaluation Using Artificial Neural Networks. *Reston, VA: ASCE [at] cProceedings of the Geo-Frontiers 2011 conference, March 13-16, 2011, Dallas, Texas| d 20110000*, 2011.
[33] Picard, R. R., and R. D. Cook. Cross-Validation of Regression Models. *Journal of the American Statistical Association*, Vol. 79, No. 387, 1984, pp. 575-583.
[34] Gevrey, M., L. Dimopoulos, and S. Lek. Review and Comparison of Methods to Study the Contribution of Variables in Artificial Neural Network Models. *Ecological modelling*, Vol. 160, No. 3, 2003, pp. 249-264.
[35] Briaud, J.-L. *Geotechnical Engineering: Unsaturated and Saturated Soils* John Wiley and Sons, New York, 2013.

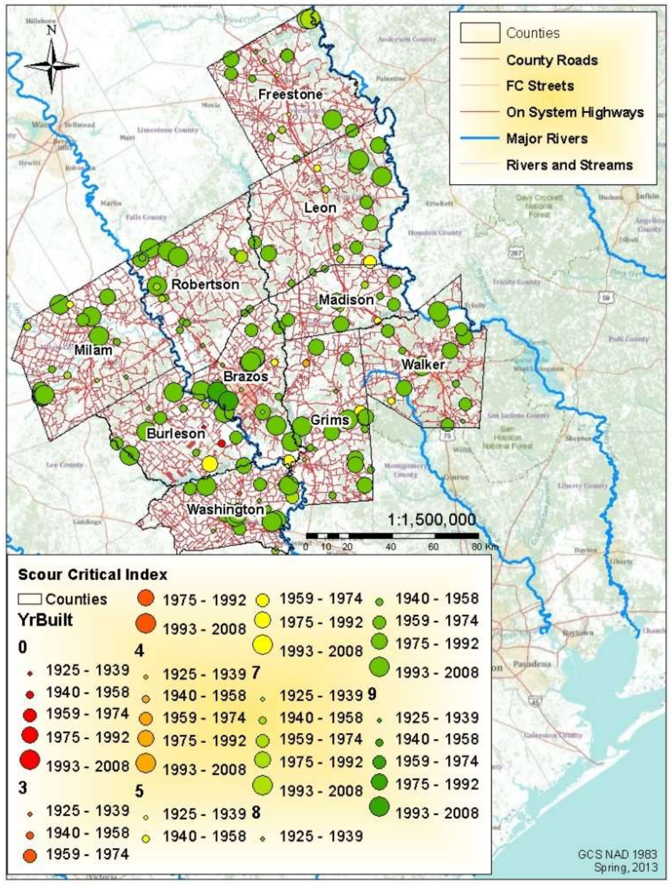


FIGURE 1 Location of 185 bridges in the Bryan District, showing the Scour-Critical Index and year built for the bridges over the ten counties.

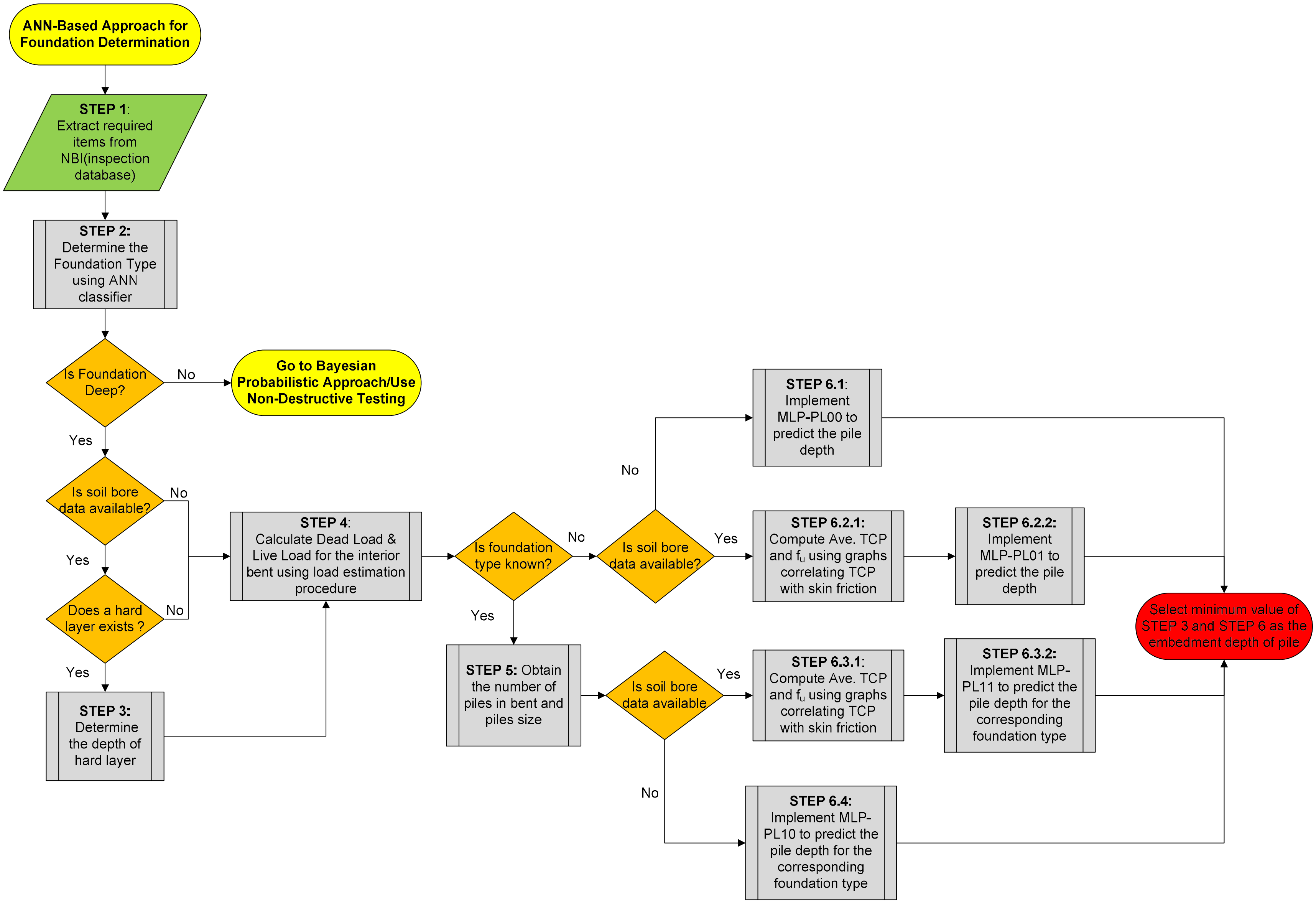


FIGURE 2 Flowchart of the proposed approach.

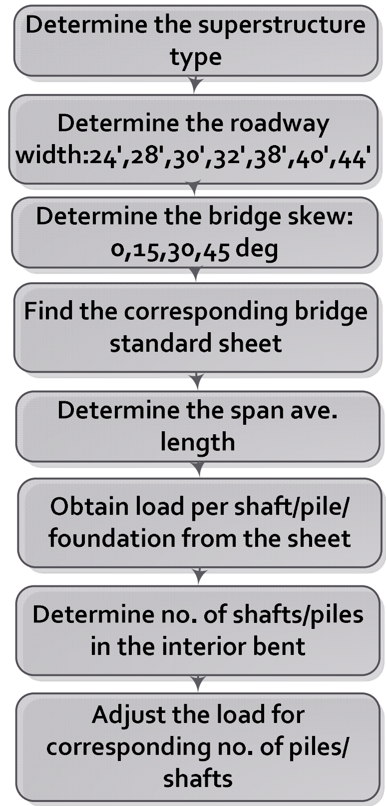


FIGURE 3 Flowchart to estimate the total load using TxDOT bridge design standard sheets.

Input Parameters
Item 3: County
Item 27: Year Built
Item 31: Design Load
Item 44-1-D1: Substructure Type above Ground for Main Span
Item 46: Total Number of Spans
Item 48: Max Span Length (ft)
Item 51: Roadway Width (ft)

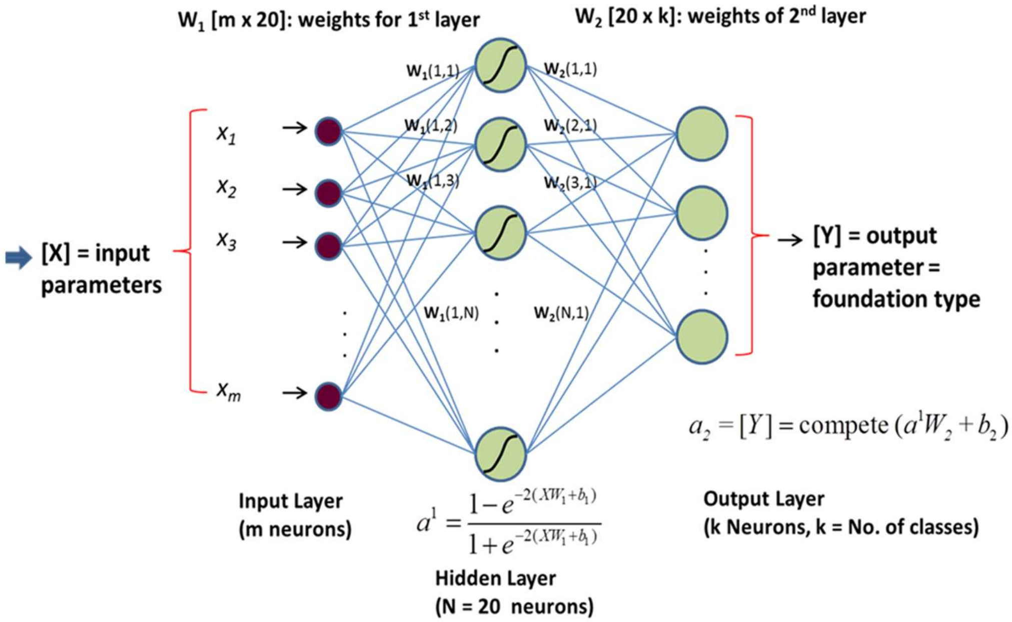


FIGURE 4 MLP network architecture and input parameters to predict the foundation type.

Input Parameters (Variables)
Load
Dead Load per bent / per pile (kN)
Live Load per bent / per pile (kN)
Geometry
Item # 51: Roadway Width (m) OR Pile Dimension/Cross Section Area (cm/cm^2)
Soil Properties
Avg. TCP (Blows/ft)
Skin Friction (MPa)
Time and Location
Item 3: County
Item 27: Year Built
Item 16: Latitude (°)
Item 17: Longitude (°)

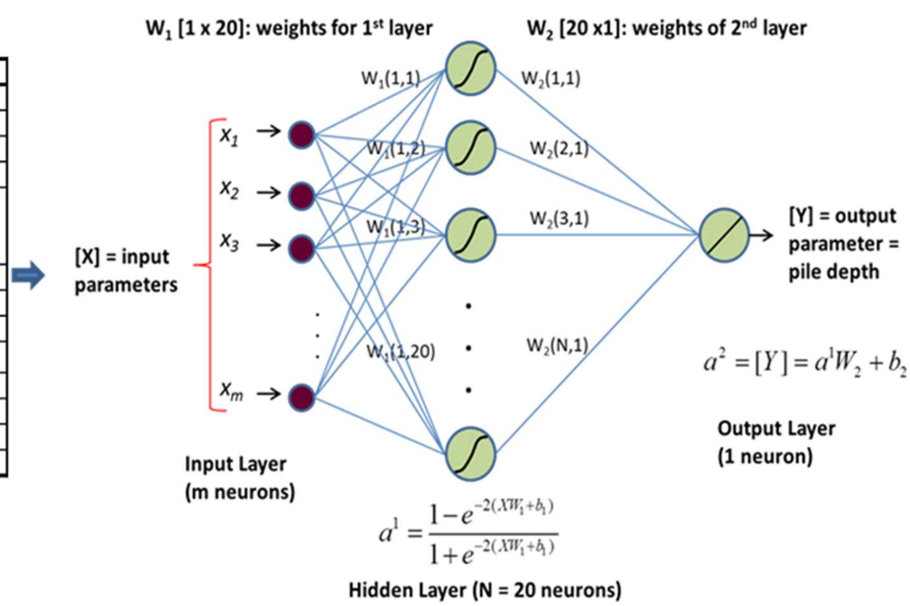
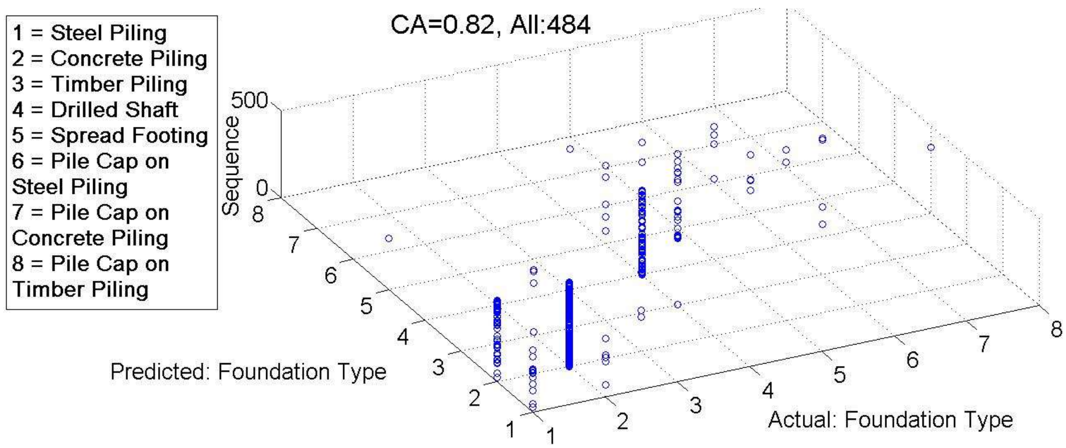
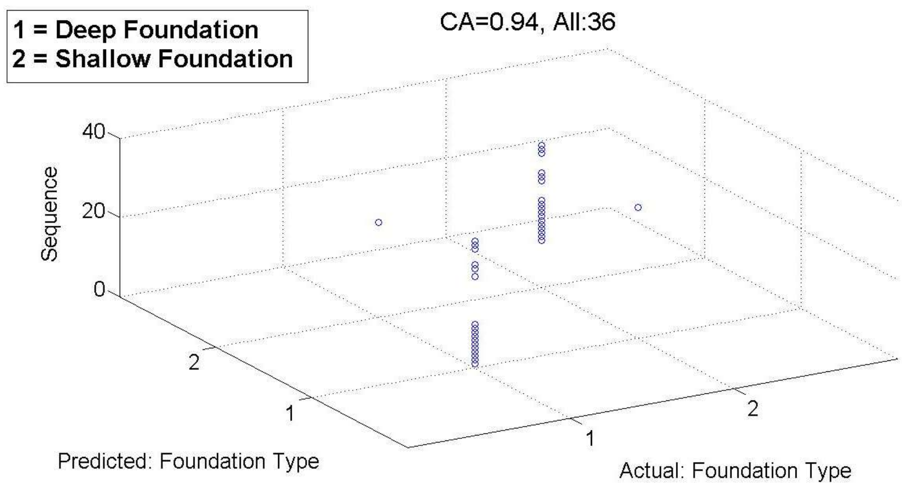


FIGURE 5 MLP network architecture and input parameters to predict the pile depth.



a)



b)

FIGURE 6 Foundation classification: predicted vs. actual scatter plots for a) MLP-FT8 and b) MLP-FT2.

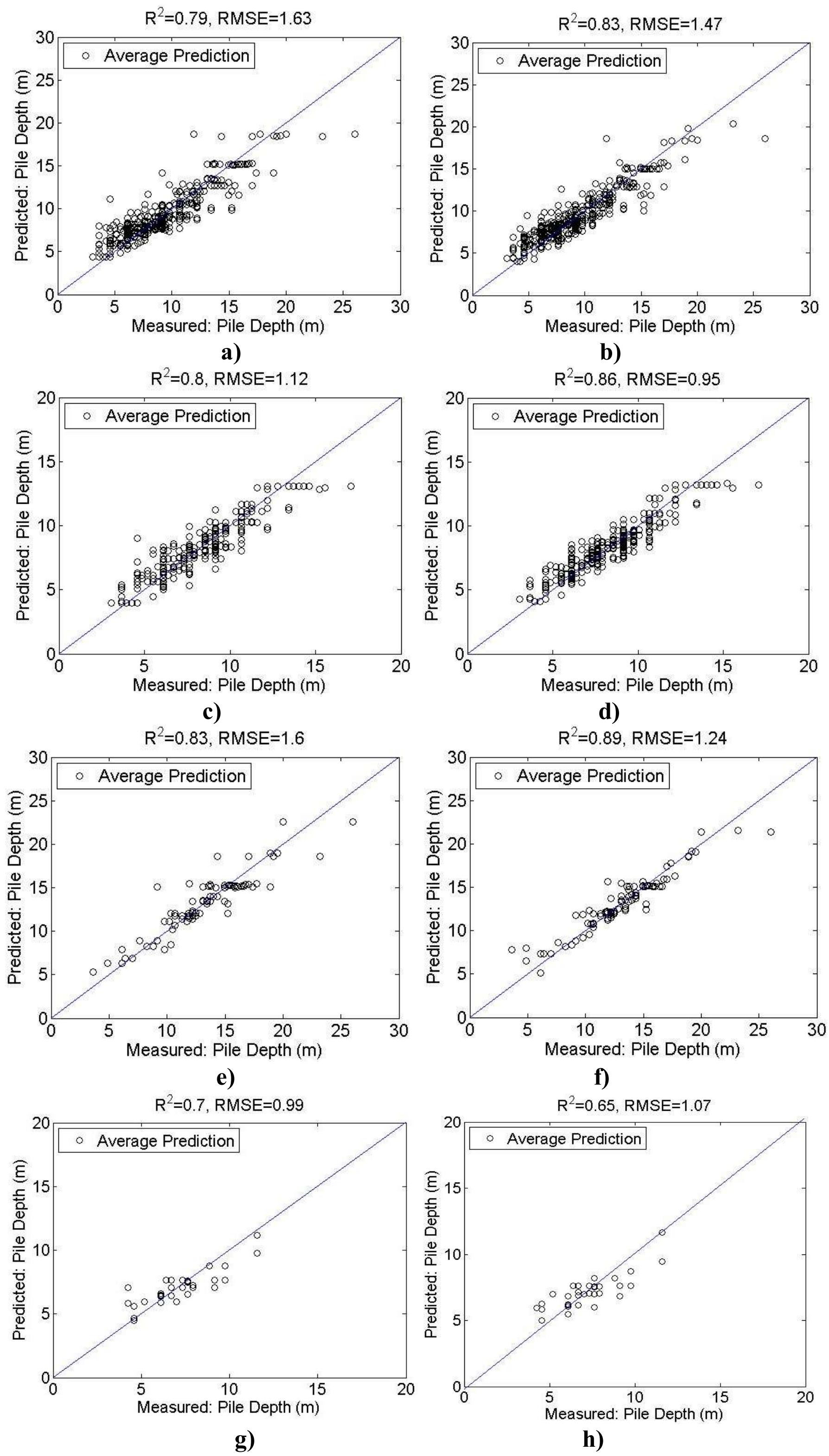
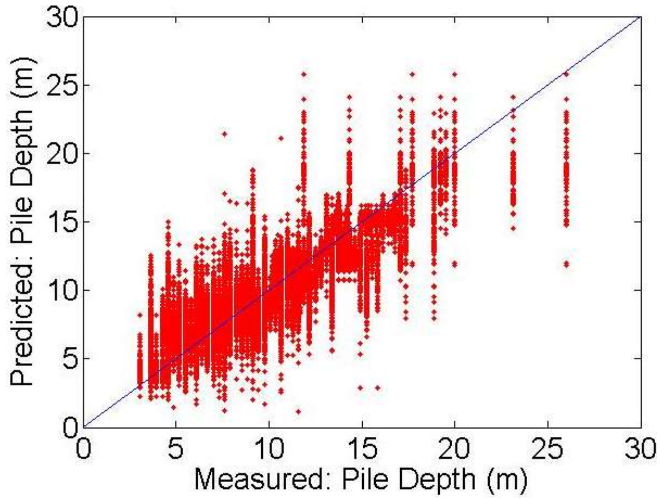
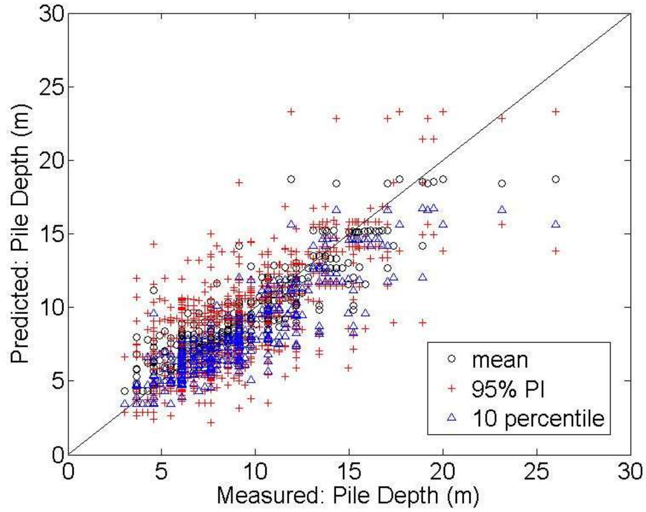


FIGURE 7 Average pile depth predictions by the MLP ensembles: a) MLPPL00, b) MLPPL01, c) MLPPL10-Conc, d) MLPPL11-Conc, e) MLPPL10-DrSh, f) MLPPL11-DrSh, g) MLPPL10-Steel, h) MLPPL11-Steel.

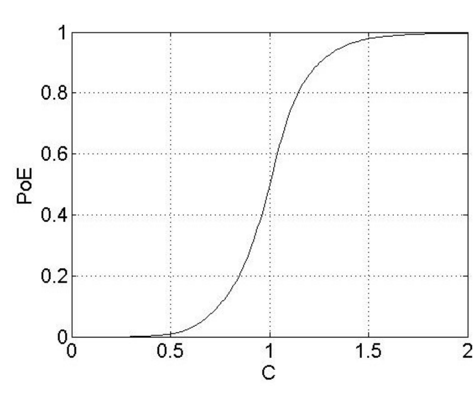


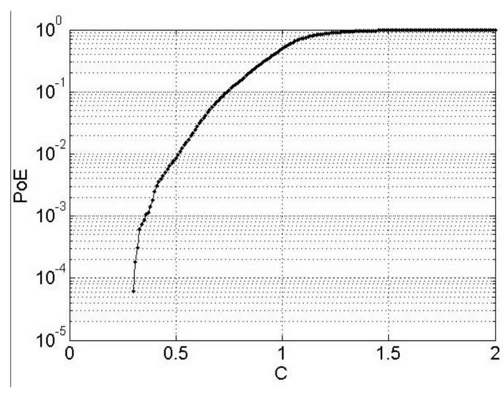
(a)



(b)

FIGURE 8 a) Predicted versus actual pile depth generated by the MLPPL00 ensemble, b) 95% prediction interval and the 10th percentile of the predicted values for pile depth,

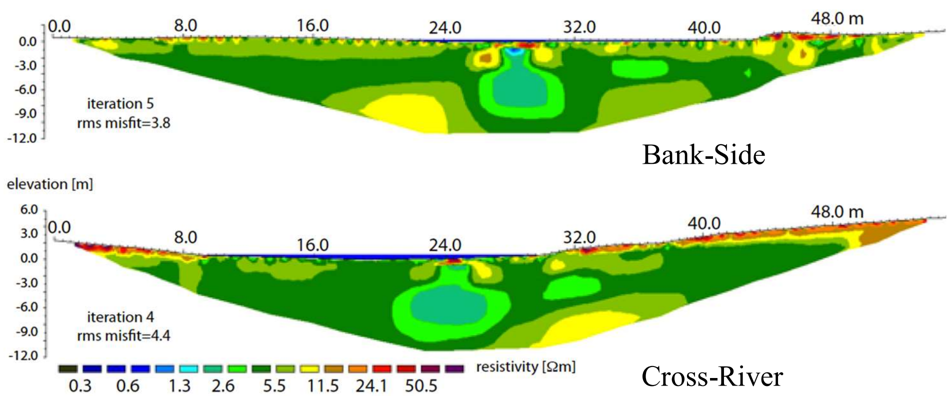




(a) (b)

FIGURE 9 a) PoE curve in normal scale, b) PoE in log scale.

(a)



(b)

FIGURE 10 a) ERI profile at the roadway bridge over Little Brazos River, b) ERI imaging results from the westbound bridge over Little Brazos River for both bank-side and cross-river profiles (*29*).

TABLE 1 List of main parameters in the database used in the models

TxDOT Bridge Inventory Item/Parameter	Min	Max	Mean	Median	Standard Deviation
Item 3: County	21	239	131.38	145	73.54
Item 16: Latitude (deg)	30.06	31.97	30.88	30.85	0.45
Item 17: Longitude (deg)	95.4	97.25	96.27	96.25	0.4
Item 26: Function Class	1	25	4.15	4	3.8
Item 27: Year Built	1922	2009	1964	1961	20
Item 29: AADT	20	31070	4470.33	1900	5445.38
Item 31: Design Load	0	5	3.44	4	1.42
Item 34: Bridge Skew (deg)	0	99	4.59	0	12.2
Item 43-1: Main Span Type	1102	2126	1232.86	1125	309.03
Item 44-1-D1: Substructure Type above Ground for Main Span	1	7	1.71	1	1.22
Item 44-1-D2: Substructure Type above Ground for Main Span	1	8	2.58	2	1.29
Item 46: Total Number of Spans	1	44	5.4	4	4.93
Item 48: Max Span Length (m)	10	240	39.73	30	25.46
Item 51: Roadway Width (m)	19	90	34.45	33.5	12.29
Item 71: Waterway Adequacy	1.12	9	6.55	6	1.16
Item 107-1: Deck Type for Main Span	1	2	1.06	1	0.24
Average TCP along Pile (Avg. TCP) (blows/ft)*	10.5	1414.75	134.47	98.7	141.81
Skin Friction (f_u) (MPa)	0.03	1.94	0.21	0.17	0.17
Dead Load (kN)	62.41	10328.36	1997.12	1317.68	1888.62
Live Load (kN)	229.65	1324.35	474.41	411.53	250.55
Pile Embedment Depth (d_p) (m)	3.05	26	9.35	8.99	3.55

* The equivalent value of TCP for 1 ft of penetration was calculated for TCP=100 with less than 1 ft penetration.

TABLE 2 Results of foundation type classification

Model	MLP-FT2			MLP-FT8		
Subset	**Training**	**Validation**	**Test**	**Training**	**Validation**	**Test**
No. of data	22	7	7	290	97	97
Ave. CA - Reduced Model	1	0.91	0.90	0.91	0.75	0.75
Ave. CA - Full Model	1	0.9	0.89	0.93	0.71	.070

TABLE 3 Case study: Input and outputs of the ANN models

Inputs	
Item 3: County	21
Item 16: Latitude (deg)	30.64
Item 17: Longtitude (deg)	96.52
Item 27: Year Built	1974
Item 31: Design Load	5
Item 44-1: Substructure Type Above Ground	341
Item 46: Total Number of Spans in Bridge	16
Item 48: Max Span Length (m)	21.34
Item 51: Roadway Width (m)	14.42
Dead Load (kN)	3716.25
Live Load (kN)	726.24
Ave TCP (bls/ft)	238.60
Skin Friction (MPa)	0.346
Outputs: $dp_{predicted\ (average)}$	
MLPPL00	10.67
MLPPL01	9.33
MLPPL10-DrSh	10.94
MLPPL11-DrSh	10.88