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TRANSPORTATION RESEARCH BOARD

The Future of Bridge Foundation Designs with Artificial Intelligence

June 22, 2021

@NASEMTRB
#TRBwebinar

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REGISTERED CONTINUING EDUCATION PROGRAM

#TRBwebinar

Learning Objectives

1. Explain significance of clean, organized datasets in enabling AI
2. Identify opportunities where design experience can be derived from data using machine learning
3. Describe the benefits of machine learning for bridge foundation design

DIGGS and AI in Bridge Foundations

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Agenda

- Technology definitions
- The significance of well-structured, high-quality datasets in enabling Artificial Intelligence (AI)
- Opportunities where design experience can be derived from data using advanced analytics
- Looking ahead

What is Artificial Intelligence

“Artificial intelligence is intelligence demonstrated by machines (or software), in contrast to the natural intelligence (NI) displayed by humans and other animals.”

Wikipedia

“The science and engineering of making intelligent machines”

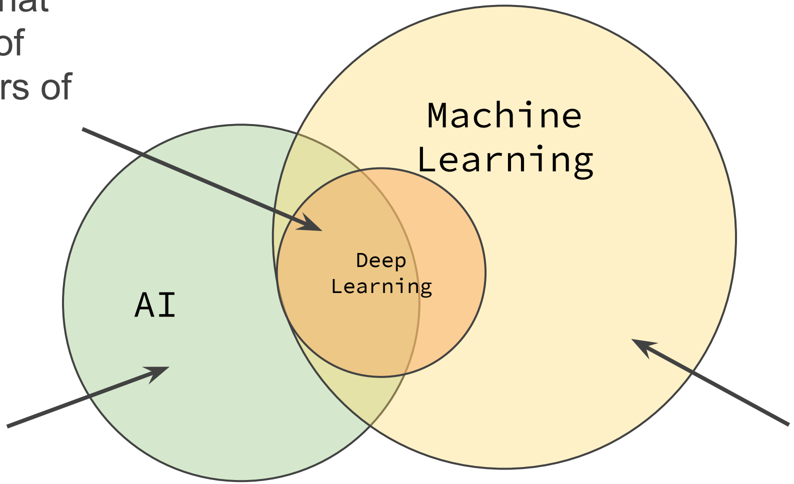
John McCarthy

“The study and design of intelligent agents, where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success.”

Russell and Norvig

Artificial Intelligence and Machine Learning

Multi-layered models that learn representations of data with multiple layers of abstraction



Rule-based intelligent systems

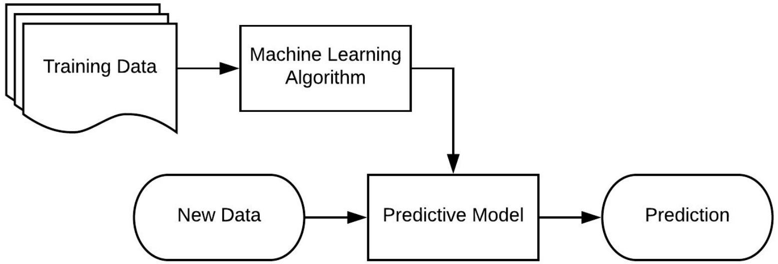
Self-learning algorithms that learn **from data**

Figure adapted from Sebastian Raschka.

What is Machine Learning

Building intelligent machines

to transform data into knowledge



The Essence of Machine Learning:

1. A pattern exists
2. We cannot pin it down mathematically
3. We have data on it

Yaser Abu-Mostafa, Learning from Data, 2012

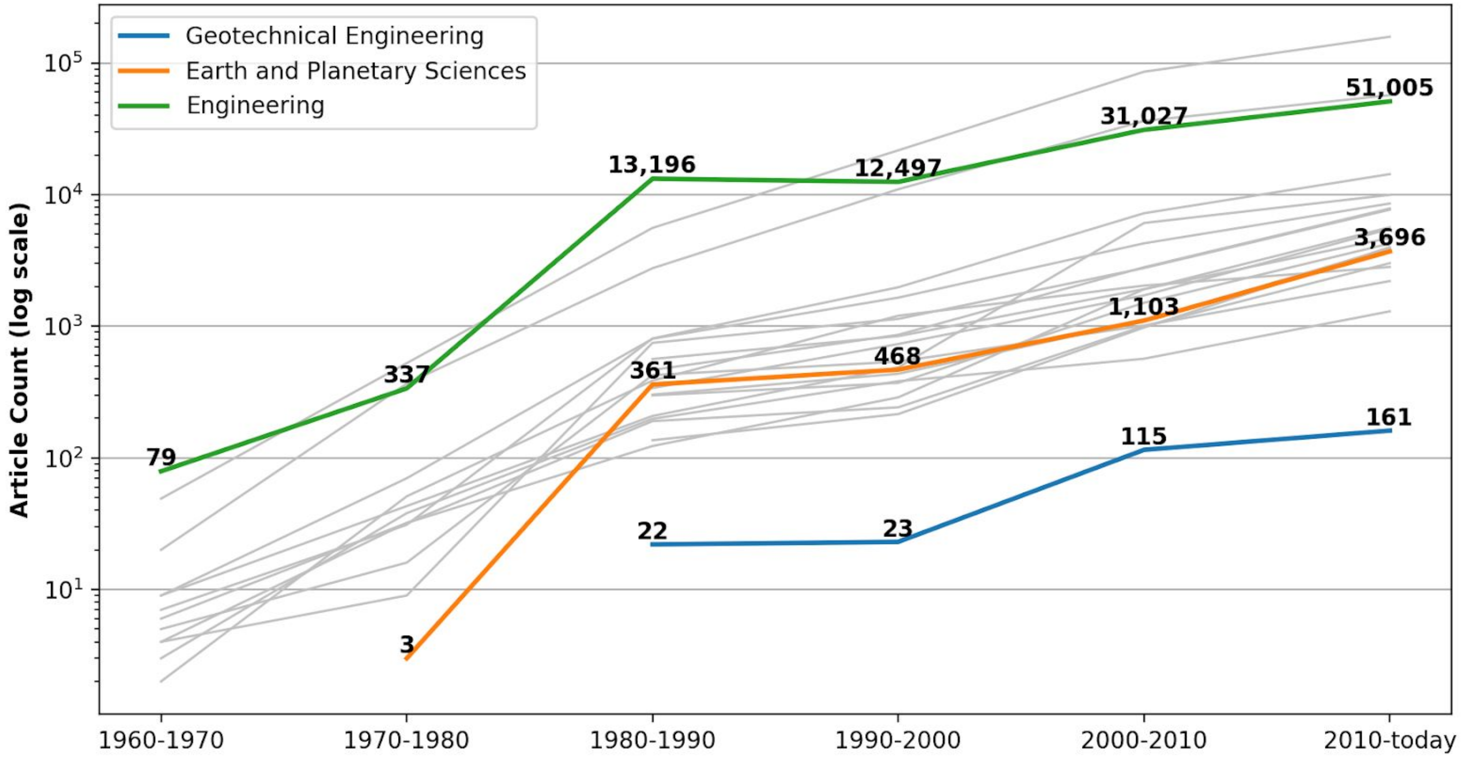
Not only AI/ML: Advanced Analytics

- Artificial Intelligence (AI) & Machine Learning (ML)
- Multivariate statistics
- Automation/optimization through computer programming
- Enhanced business intelligence (BI)
- Data mining
- Simulations
- …

Prerequisite: High-quality Data

- High-quality, structured data is the new **currency** and the **fuel** that powers Machine Learning
- Example from other industries: The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was a catalyst to the evolution of Deep Learning
- State of open deep foundation datasets: Little uniformity, highly dissimilar, unstructured, semi-structured or structured with little to no data validation; incompatible with ML requirements

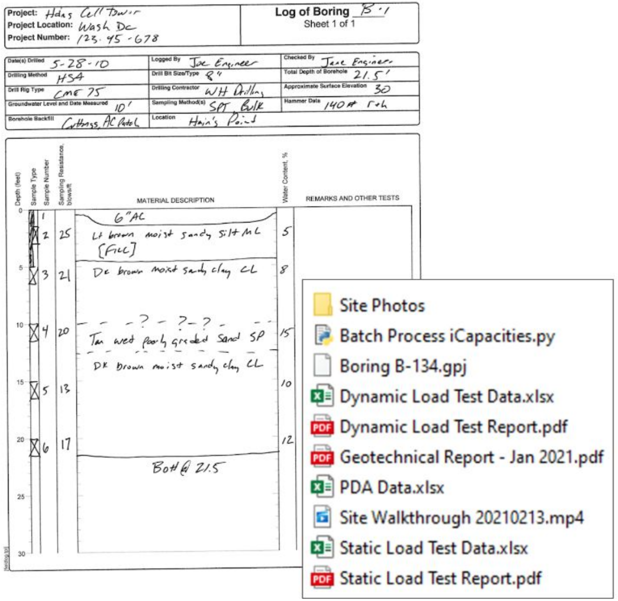
Research activity



Bridge foundation projects generate lots of data

- Geotechnical - site investigation
  - Boring logs
  - Geophysical testing
  - In-situ testing
- Inspection records
- Construction records
- Remote sensing
- 3D Modeling (AR/VR)
- Load testing
  - Static
  - Dynamic
- Installation
  - Pile driving behavior
  - Pile driving equipment
- Construction records
  - Precast specs
  - QA/QC
  - Performance monitoring

Data structures



id	first_name	last_name	email	job_title
1	Helga	Ferrara	hferrara0@shin	Chemical Engineer
2	Chickie	Coppen	ccoppen1@huge	Operator
3	Odey	Harnett	oharnett2@diig	Cost Accountant
4	Kahlil	Cheesman	kcheesman3@c	Staff Scientist
5	Julian	Hryskiewicz	jhryskiewicz4@	Office Assistant III
6	Joya	Rickford	jrickford5@yell	Help Desk Technician
7	Allyn	Drust	adrust6@1und1	Legal Assistant
8	Angy	Binner	abinner7@ama	Chief Design Engineer
9	Shauna	Heaselgrave	sheaselgrave8@	Financial Analyst
10	Wallie	Picard	wpicard9@blog	Physical Therapy Assistant
11	Berthe	Harp	bharpa@admin.	Financial Advisor
12	Anny	McIllroy	amcillroyb@mo	Data Coordiator
13	Magdalena	Scotti	mscottic@mapc	Community Outreach Speci
14	Lily	Chaudret	lchaudretd@wo	Developer IV
15	Mariann	Normanell	mnormanelle@	Developer I

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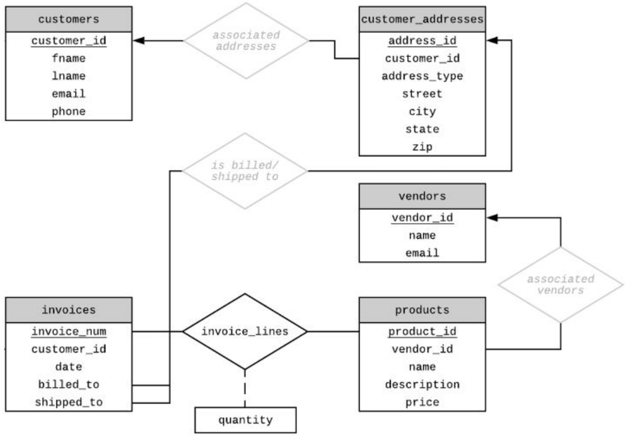


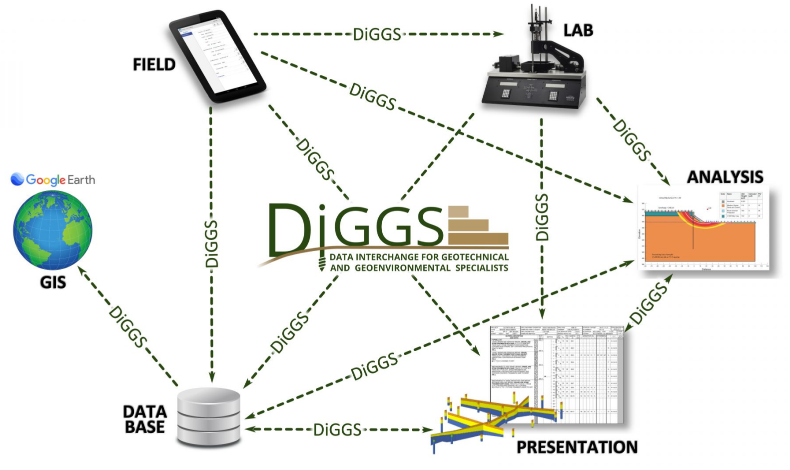
Unstructured

Semi-structured

Structured

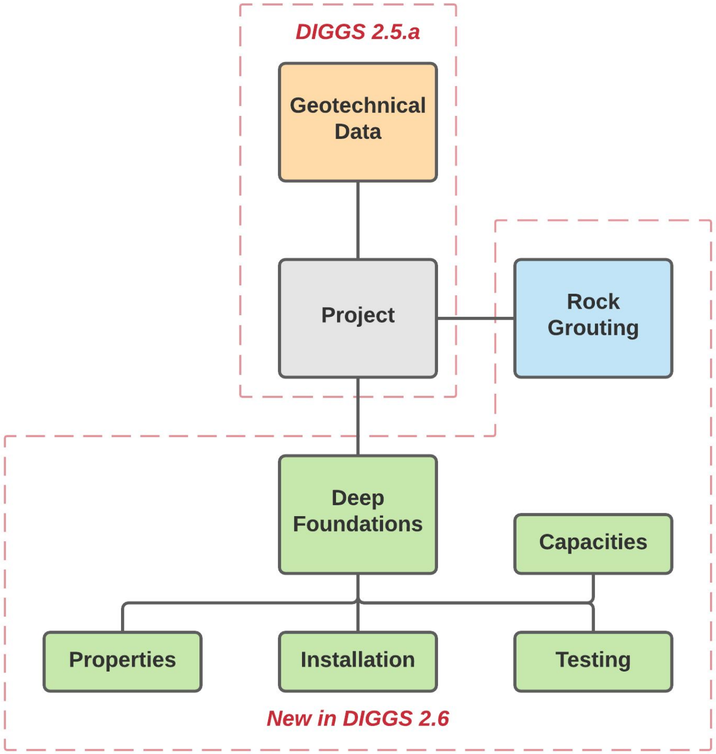
DIGGS

- Data Interchange for Geotechnical and Geoenvironmental Specialists
- GML (XML-based) geospatial standard schema for the transfer of geotechnical and geoenvironmental data
- Enter data once, use anywhere DIGGS is supported
- Backed by ASCE, FHWA

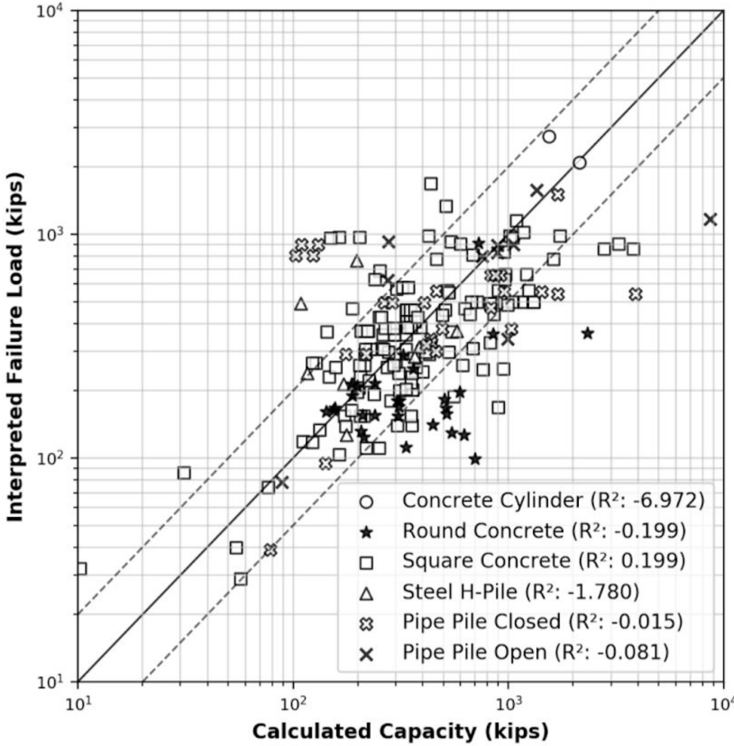


DIGGS (cont.)

- Extensible schema
- A single file can hold details on multiple projects
- Can be parsed/generated programmatically
- Great for large-scale analyses, machine learning



Bridge foundation design challenges



- Wide scatter in nominal vs interpreted capacities
- Semi-empirical, empirical design methods, based on the behavior of a few dozen piles
- Experience from past projects is transferred through people, not data, and often lost
- Missing the data structure, tools and methods to analyze at scale

Hypothesis

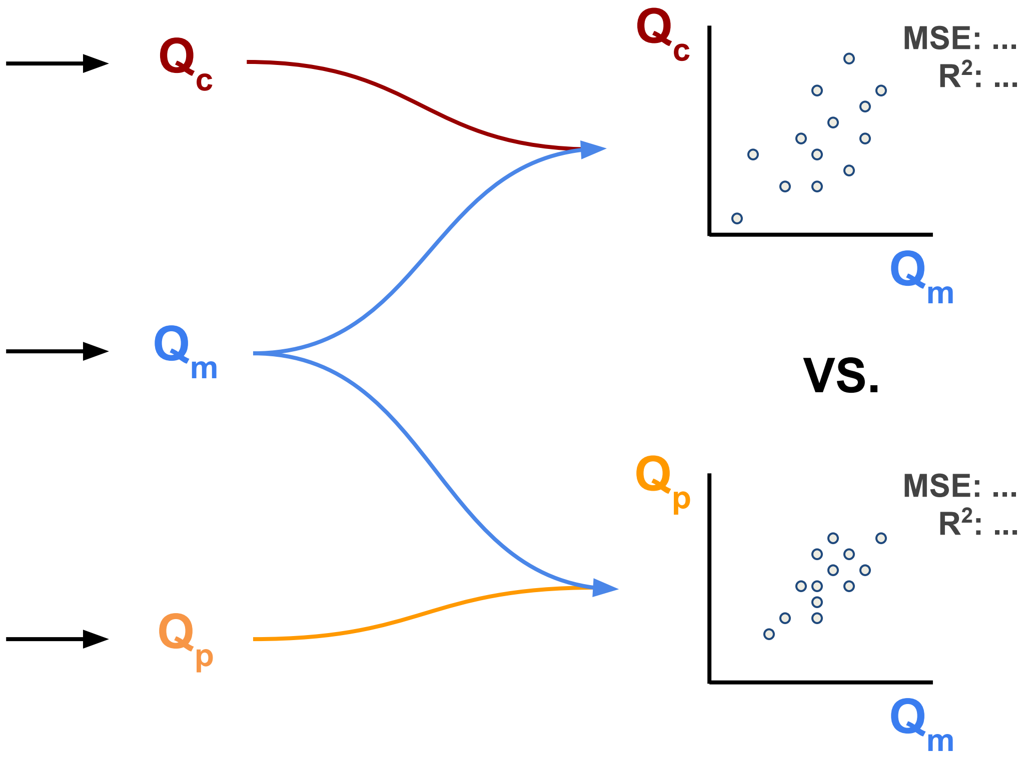
R_n Nominal Capacity		R_m Interpreted Capacity
i.e. **4,000 tons**	$R_n \approx R_m$	**1,000 - 16,000 tons**

Can advanced analytics workflows lead to:

- Accurate interpreted capacity
- Reliable calculated capacity
- Case-based design

Prediction PoC

1. Calculate capacity using Nordlund and Tomlinson
2. Interpret capacity from static load test using the Davisson criterion
3. Predict capacity using M/L (SVR model)



Feature Selection

SOIL

1. **Soil type** (sand, clay, mixed) - categorical
2. **Average N count** - numerical*

** intentional oversimplification; not ideal, but the quality of the available soil data does not justify the additional computational effort of using a layered system*

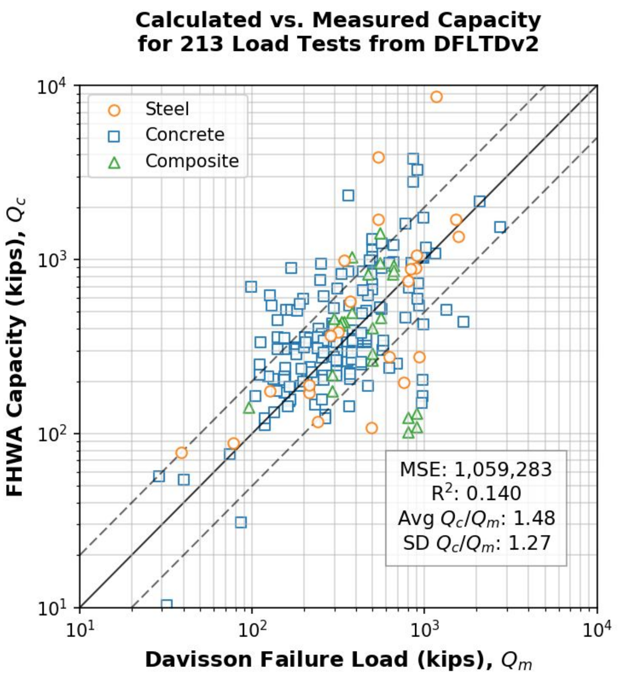
PILE

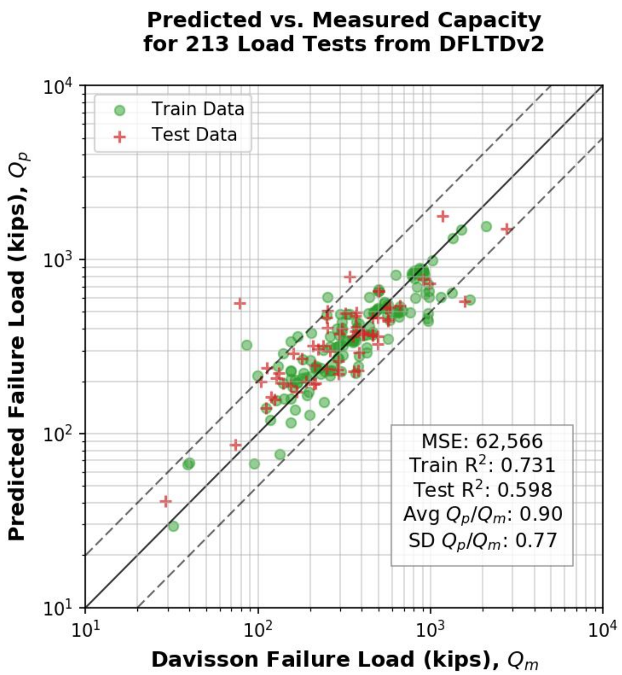
1. **Pile material** (steel, concrete, composite) - categorical
2. **Pile end** (open/closed) - categorical
3. **Cross sectional area** - numerical
4. **Circumference** - numerical
5. **Length** - numerical

Three (3) categorical and four (4) numerical features

Results

- MSE reduced by a factor of 17 (62,566 kips)
- MPE improved by a factor of 2 (-47.78% to -25.7%)
- Absolute MPE reduced (76.3% to 42.3%)
- Test R^2 was 0.6 (or 60%). The model yields errors that are 45% smaller than those of a constant-only model, on average. An improvement on errors by a factor of 9.





Results of predicted capacity compared to measured capacity. Absolute MPE with real-value MPE in parentheses (RHS legend)

Recommendation PoC

Example

- 10-inch side
- 51-ft long
- HPILE
- Mixed Soil Conditions

Analytical workflow

- Compute capacity or use stored values
- Offer **design insights** by running aggregate analyses for similar records

Pile Information

Type:	HPIL	**Total Length:**	51.0 ft	**Weight:**	n/a
Shape:	HP 10X42	**Embedded Length:**	51.0 ft	**Square Circ.:**	n/a
Diameter/Side:	10.0 in	**AE/L:**	n/a	**Cross Sec. Area:**	12.4 sq.in
Wall Thickness:	n/a	**Modulus:**	n/a		
Circumf./Perimeter:	n/a	**Displacement Ratio:**	n/a	**Head Elevation:**	n/a
Date Driven:	1973-08-21	**Design Load:**	37.0 kips	**Toe Elevation:**	759.7 ft
Name:	n/a	**Predrill Depth:**	n/a		
Description:	n/a				

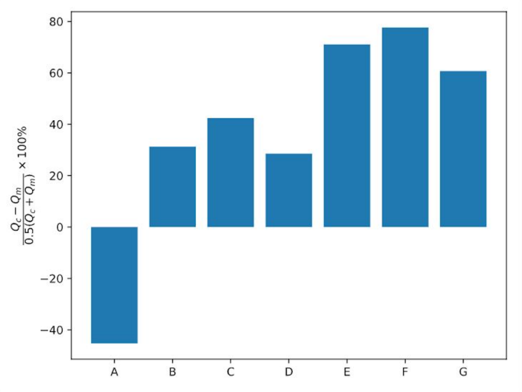
Taper: n/a **Vibro:** n/a **Cased:** n/a **Predrill:** n/a **Relief:** n/a **Jetted:** n/a

Calculated Capacities

Plot Legend	Type	Capacity (kips)
A	Iowa DOT Modified ENR (bearing) (source DB)	49.20
B	Iowa Theoretical Capacity (source DB)	106.92
C	Iowa Blue Book Method (source DB)	120.00
D	Meyerhof (source DB)	104.00
E	API 1984 (source DB)	164.00
F	Beta Burland 1973 (source DB)	177.00
G	Nordlund (source DB)	146.00

Design Insights
There are **25** similar records in *NYU Pile Capacity*. Click here to review the aggregate analysis.

% Difference from Q_m (Std. Davisson)



In conclusion

- Reducing the inherent complexity of data management and analysis enables interactivity and flexibility to investigate new areas
- Hypothesis is confirmed: more/better data and advanced analytics can lead to better bridge foundation designs
- There is no AI without high-quality, well-structured data
- Identify and empower citizen data scientists within your organization
- Get leadership on board and seek the advice of experts

Looking ahead

- Proof of concept (PoC) studies on AI are excellent, and there is an increasing number of them
- As AI is adopted and becomes more mature in our field, the focus will be on reliable applications rather than PoC
- Industry leaders will eventually compete on AI, and decision makers at the state/federal level might have to step in to set standards

Webinar: Artificial Intelligence and Bridge Foundation Design

Evaluating the Ultimate Pile Capacity from Cone Penetration Test (CPT) Data using Artificial Neural Network

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June 22, 2021

PRESENTATION OUTLINE

- ❑ Introduction
- ❑ Objectives of the study
- ❑ Cone Penetration Test
- ❑ Overview of ANN
- ❑ Evaluation of Ultimate Pile Capacity from CPT Data
- ❑ Pile Load Tests Database
- ❑ Development of Neural Network Model
- ❑ Results of ANN Modeling
- ❑ Sensitivity Analysis of ANN model Inputs
- ❑ Comparison with Traditional Pile-CPT Methods
- ❑ Limitations of Study
- ❑ Conclusions

INTRODUCTION

- Over the years, many analytical and empirical pile design methods were developed [e.g., Static analysis methods using total or effective stresses (α, β, γ), Methods based on SPT data, Methods based on CPT] for different soil types based on lab or in-situ field test data.
- These methods usually relate the pile capacity to different soil properties, which are evaluated from laboratory and/or in-situ field tests that include soil borings/layering, undrained shear strength, friction angle, soil classification, etc.
- Conducting laboratory tests is expensive and time consuming.

INTRODUCTION

- Many direct pile-CPT methods were developed in the last few decades to estimate the ultimate pile capacity form CPT data (q_t,f_s), such as: Schmertmann, De Ruiter and Beringen, LCPC (Laboratoire Central des Ponts et Chaussees), probabilistic, UF (University of Florida) and many other CPT methods.
- Most of the pile design methods involve several correlation assumptions and judgments in selecting the proper correlation coefficients, which can influence the calculation of ultimate pile capacity, that can result in inconsistent accuracy of pile capacity for different soil/pile conditions.

INTRODUCTION

- To resolve the shortcoming in traditional direct pile-CPT methods, the ANN concept can be introduced to develop models to estimate the pile capacity from CPT data, since it does not need any correlation assumptions or judgements.
- The ANN method usually learns from previous cases/instances and trains by using special mathematical algorithms.
- The developed ANN models are expected to yield better and consistent accuracy in estimating the ultimate pile capacity from CPT data.

OBJECTIVES OF THE STUDY

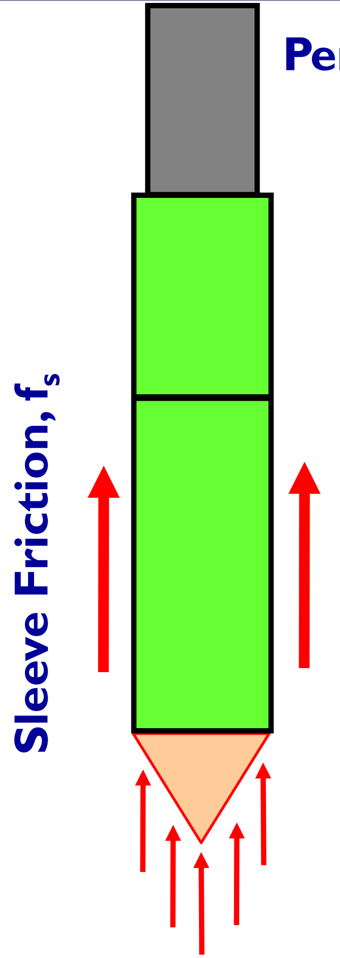
- ❑ Explore the applicability of ANN in predicting the ultimate axial capacity of piles from CPT data.

- ❑ Evaluate the relative importance of different input parameters, e.g. q_t, f_s, embedment pile length, L, and pile width, B.

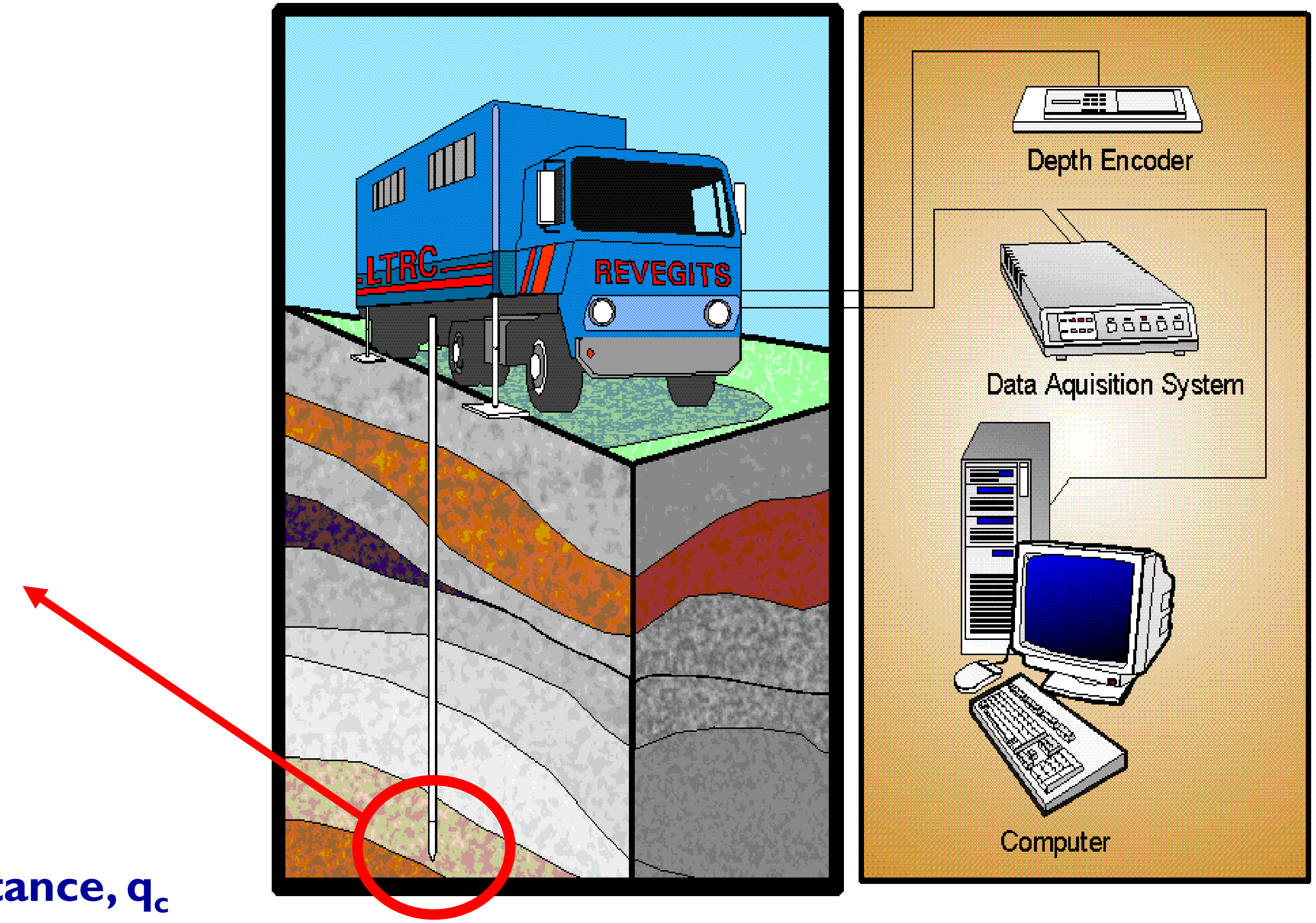
- ❑ Compare the ANN results with the well-performed direct pile-CPT methods.

- ❑ Evaluate the ANN models within the context of LRFD reliability analysis to demonstrate their accuracy and bolster their reliability and feasibility.

CONE PENETRATION TEST (CPT)



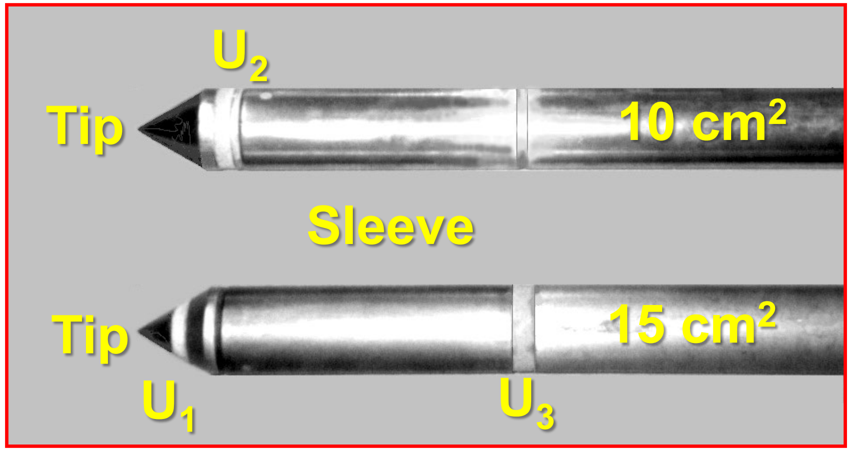
Penetration Rate: 2 cm/sec



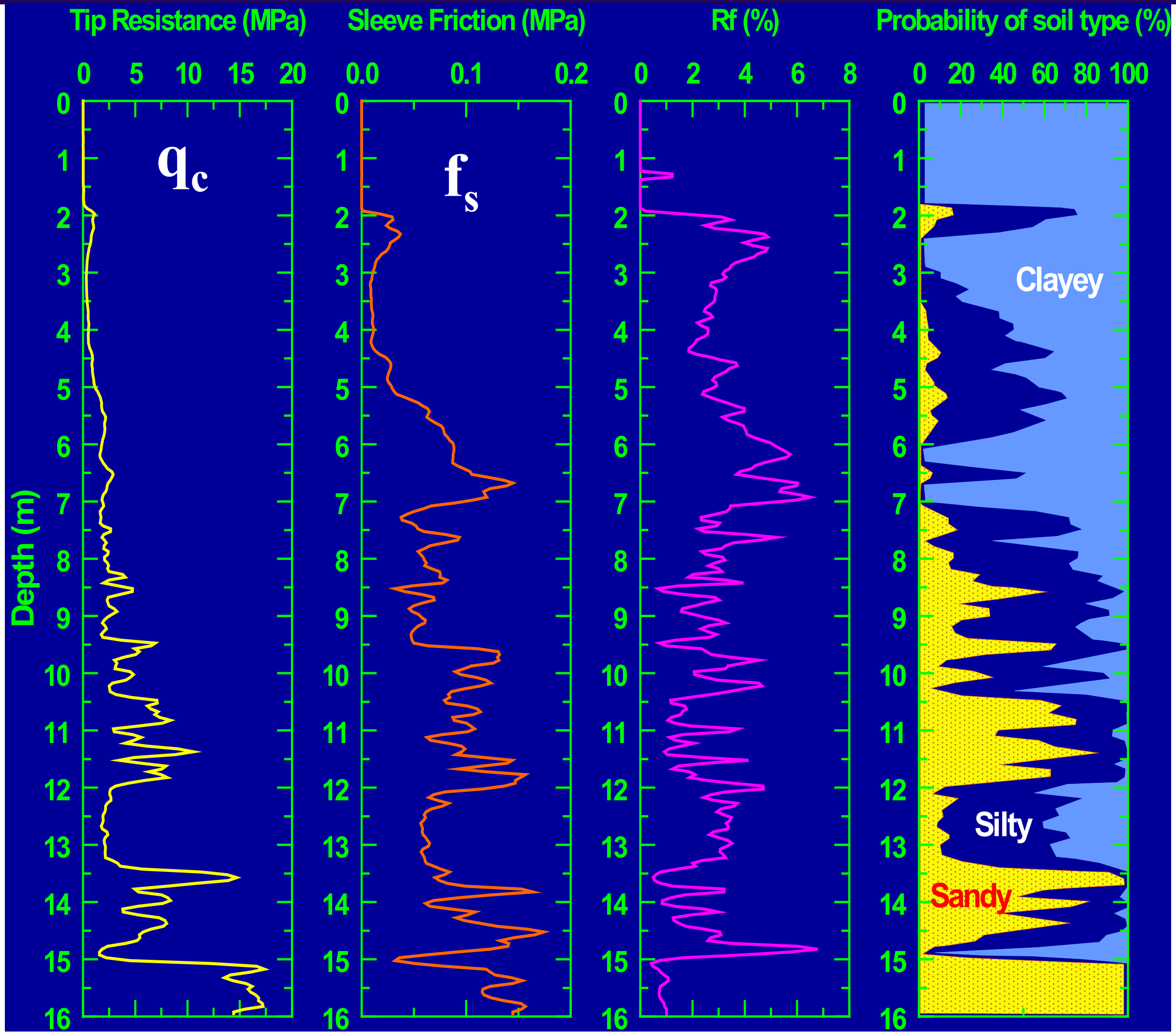
Base area = 10 cm²
Sleeve area = 150 cm²
Cone angle = 60º

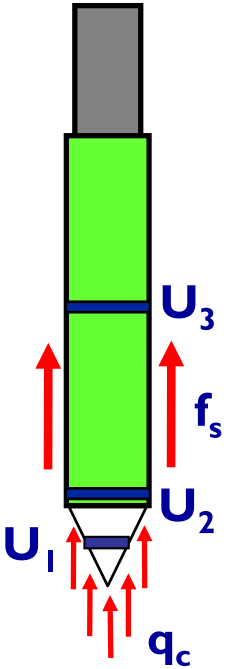
Cone Tip Resistance, q_c

CPT TRUCK AND PENETROMETERS



TYPICAL CPT TEST DATA



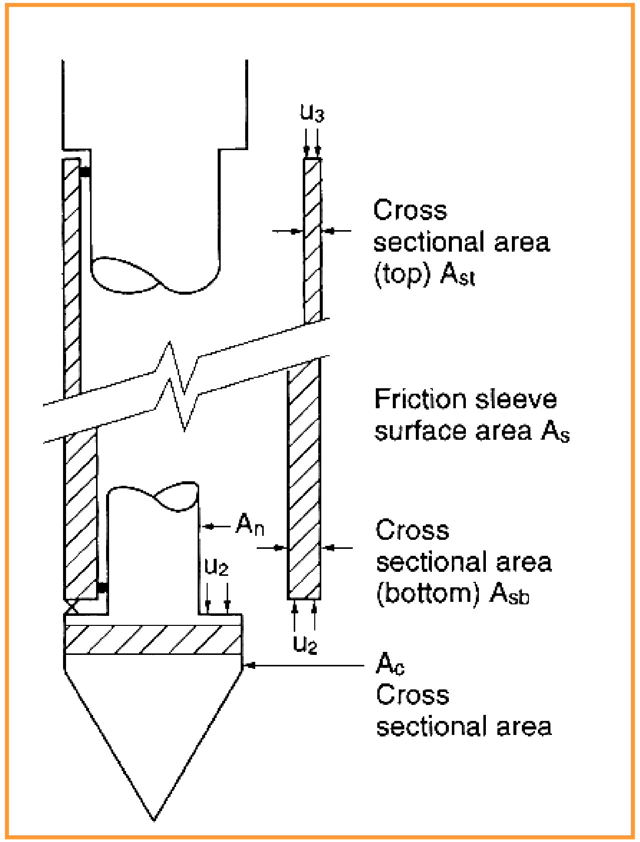


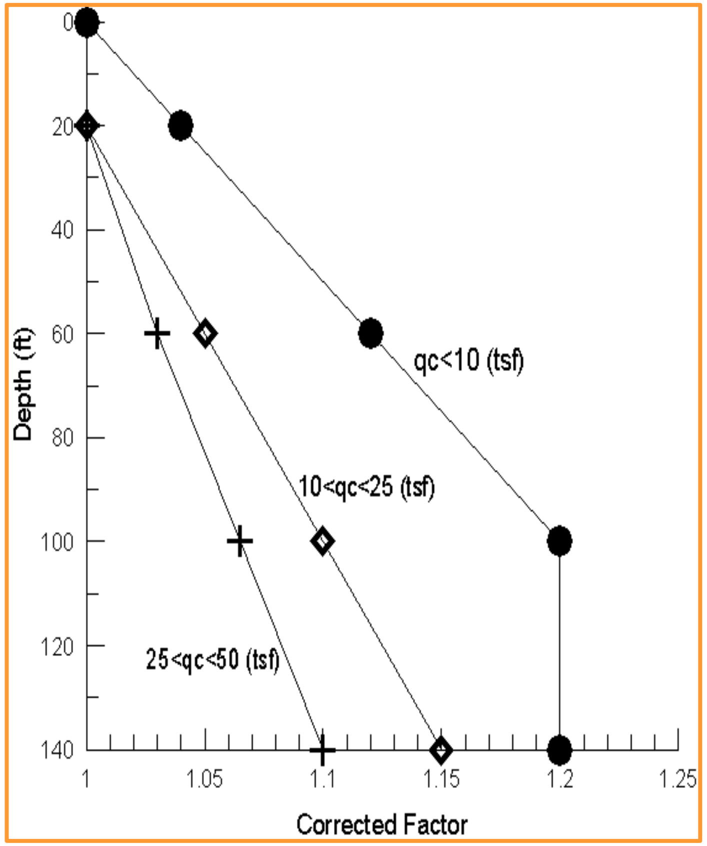
TYPICAL CPT TEST DATA

$q_t = q_c + u_2\ (1 - a)$
$a = A_n/A_c$

q_t = corrected cone resistance
q_c = measured cone resistance

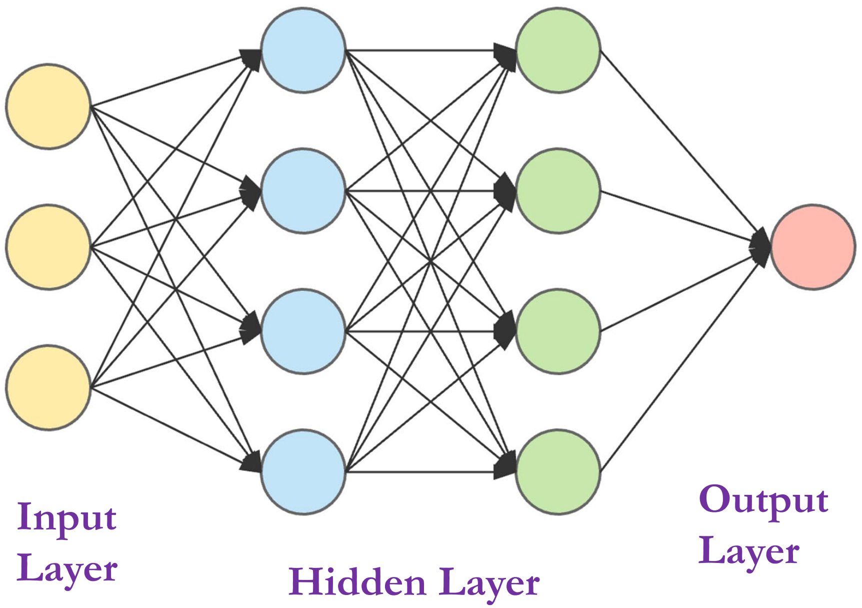
a = effective cone area ratio
A_n = cross-sectional area of the load cell
A_c = area projected by the cone





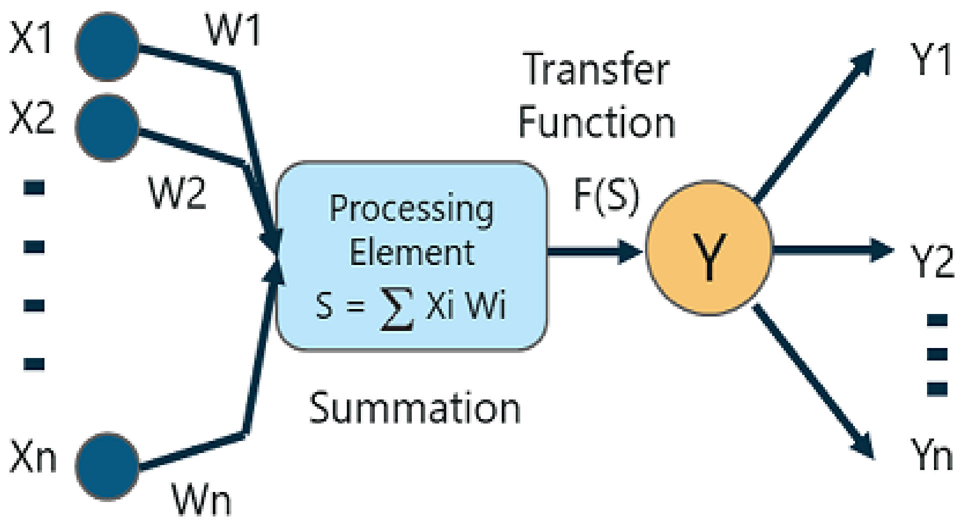
OVERVIEW OF ARTIFICIAL NEURAL NETWORK (ANN)

- The artificial neural network (ANN) models are trying to mimic the learning system of humans brain, which is composed of complex webs of interconnected neurons, using mathematical algorithms.
- So, the ANN is composed of complex webs of interconnected neurons/nodes, the primary elements of Artificial Neural Network.
- Usually the ANN model consists of an input layer, one or a more intermediate/ hidden layers, and an output layer.
- The network is arranged in a way that, the output of one layer serves as the input for the following layer.
- The ANN can performs parallel computation for complex and massive data processing.



OVERVIEW OF ARTIFICIAL NEURAL NETWORK (ANN)

- The nodes of each layer are connected to other node elements through weighted connections. Between the interconnected neurons, the corresponding weights represent the strength of the connections.
- An individual processing node receives weighted inputs, which are then summed and propagated through a transfer function (e.g., step, linear, ramp, logistic sigmoid or hyperbolic tangent) to generate the output of the neuron.
- For any node *j* in layer *l*, the summed process can be summarized using the following equations:



$$I_j^l = \theta_j^l + \sum_{n=1}^{i} w_{ji}^l x_i^{l-1} \qquad y_j^l = f(I_j)$$

where, I_j^l = activation level of node j; w_{ji}^l = connection weight between nodes i and j; x_i^{l-1}= input from node i; i = 0, 1, …, n; $\theta_j^l = w_{j0}$= bias for node j; y_j^l = output of node j; and $f(I_j)$ = transfer function.

OVERVIEW OF ARTIFICIAL NEURAL NETWORK (ANN)

- The difference between the obtained output and the target output is the Error, E

  $$E = \tfrac{1}{2}(\mathbf{Output}_{\mathbf{Target}} - \mathbf{Output}_{\mathbf{obatined}})^2$$

- The Error is then distributed backward through the weights starting from the output layer towards the input layer.
- The weights, w, are then adjusted with respect to the corresponding error as follows:

  $$w_{new} = w - \eta * \frac{\partial E}{\partial w}, \quad \eta \text{ is the learning rate}$$

- The network propagation is repeated with the updated weights until the obtained output is close enough to the target output (within acceptable tolerance).

OVERVIEW OF ARTIFICIAL NEURAL NETWORK (ANN)

According to Structure

- *feedforward* networks
  - Flow is unidirectional starting from input layer to output layer.
  - No connections are allowed between neurons in same layer.
- *Recurrent* networks
  - Outputs of some neurons are fed back to same neuron (connection loops) or to other neurons in preceding layers.

According to learning paradigm

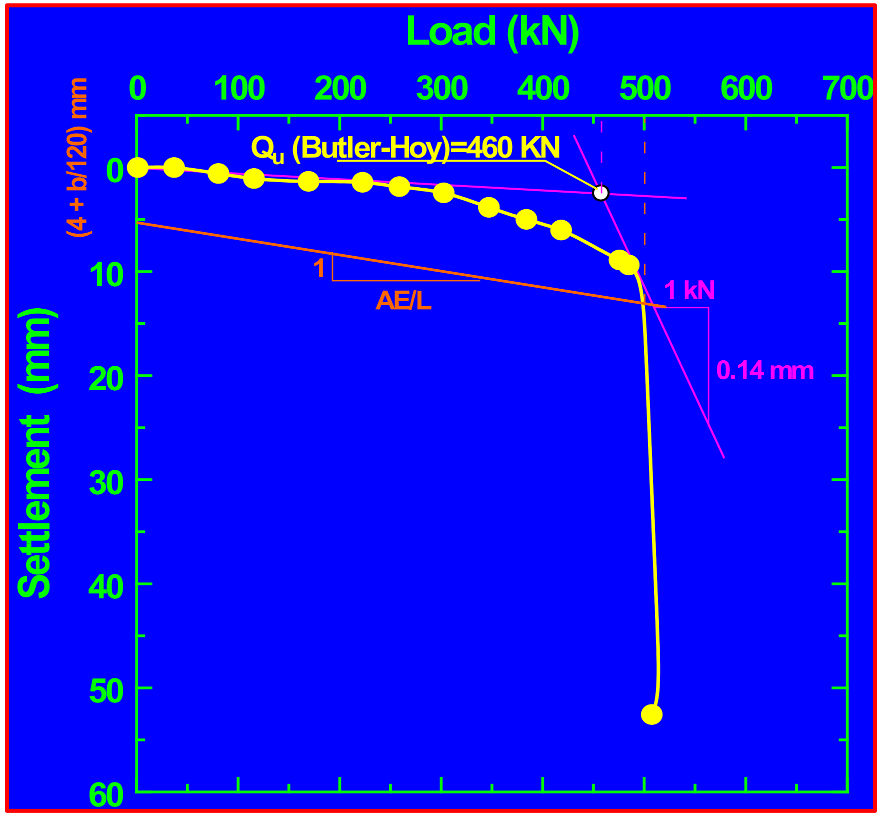
- *Supervised Learning*
  - Network is provided with correct answers for input patterns. The connection weights are adjusted to allow the network to produce answers as close as possible to target answers.
- *Unsupervised Learning*
  - Does not require desired outputs. Learning proceeds by clustering input patterns into categories of similar features.
- *Reinforcement Learning*
  - This is a special case of supervised learning in which the network is provided only with a critique on the *goodness* of network outputs for a given input pattern rather than true answers.

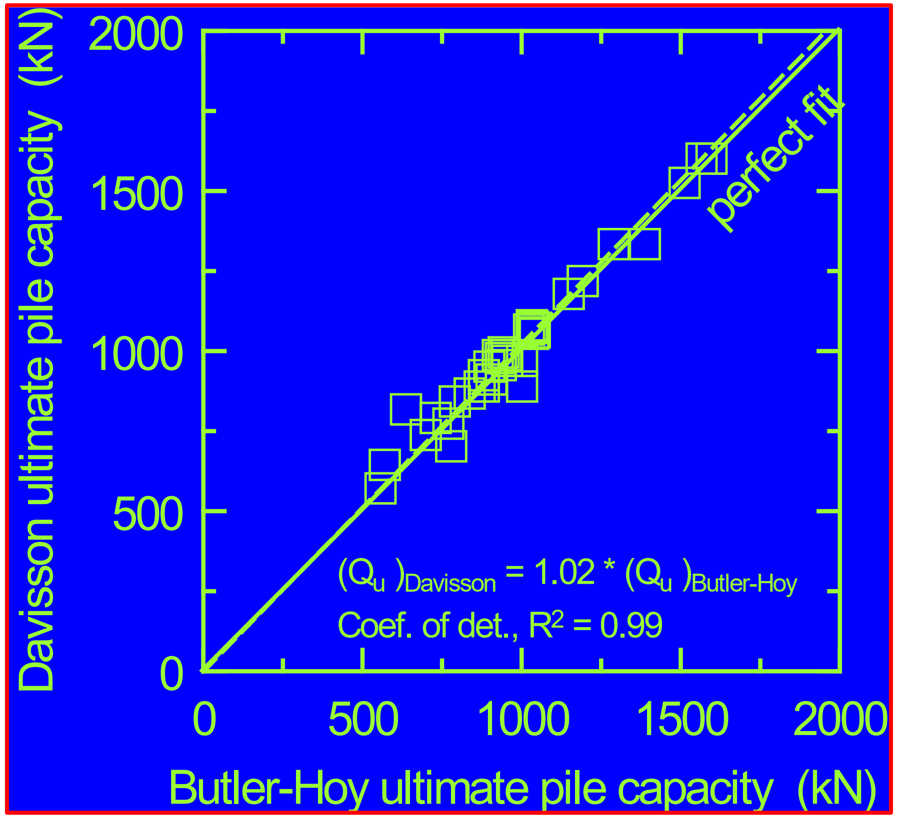
ESTIMATION OF ULTIMATE AXIAL PILE CAPACITY

- Static pile load tests: Davisson, Modified Davisson, Butler-Hoy, DeBeer, VanDer Veen, etc.
- Static analysis: α-Tomlinson method, Nordlund method (from Borings), etc.,
- Dynamic analysis: PDA, CAPWAP (EOD, Restrikes), GRL WEAP, CASE, etc.,
- Statnamic load tests,
- In-situ test methods: SPT, CPT, etc.

INTERPRETATION OF STATIC PILE LOAD TESTS

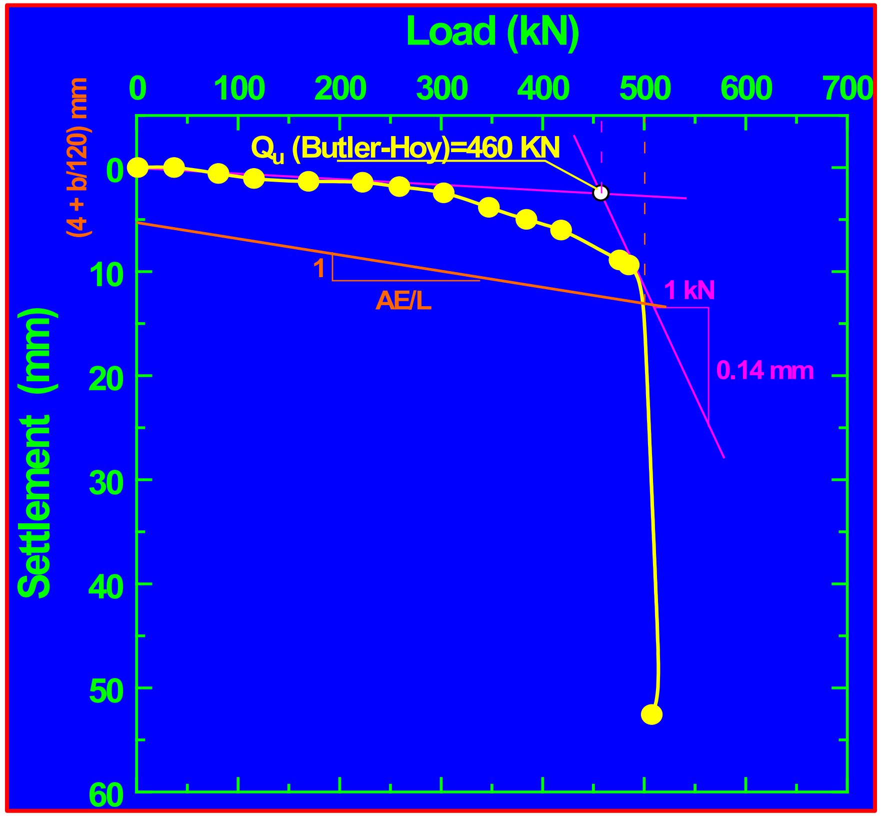
- ❑ Davisson method
- ❑ Butler-Hoy method

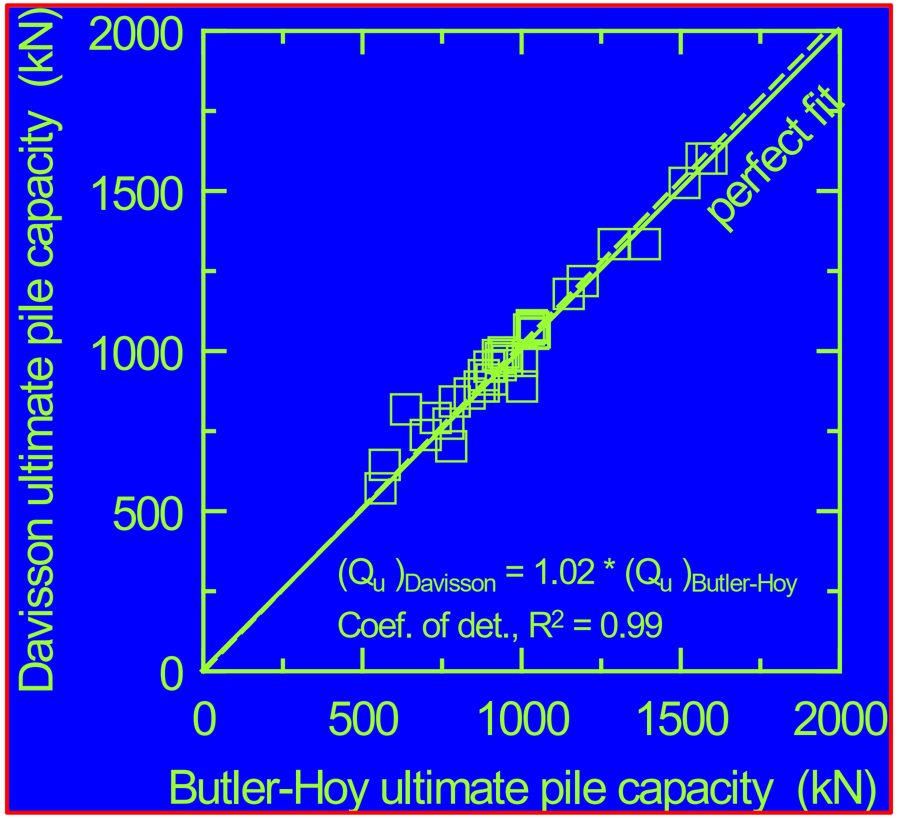




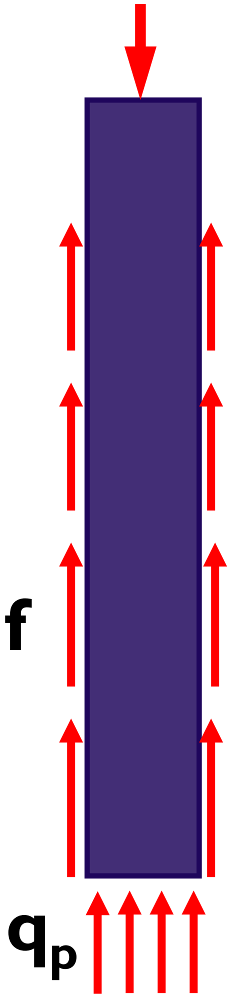
INTERPRETATION OF STATIC PILE LOAD TESTS

- Davisson method
- Butler-Hoy method





ULTIMATE AXIAL PILE CAPACITY



$$Q_{ult} = Q_p + Q_s$$

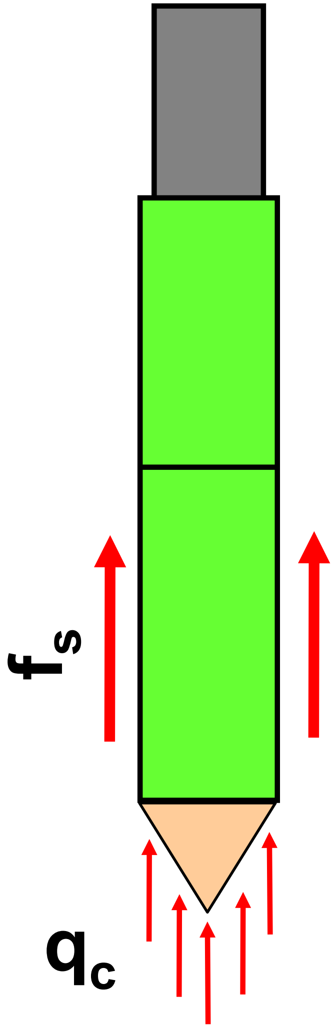
Shaft friction capacity,

$$Q_s = \Sigma\,(f_i \,.\, A_{si})$$

End bearing capacity,

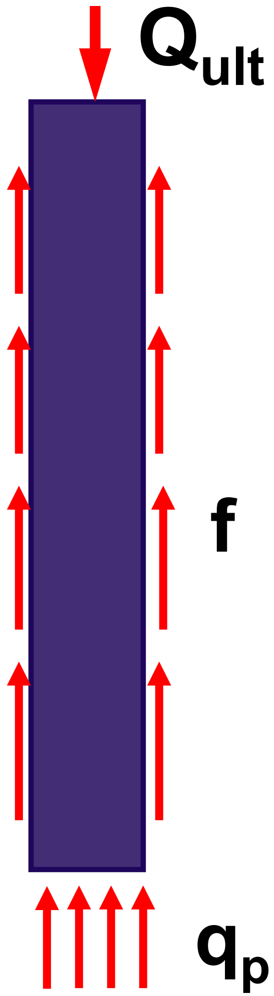
$$Q_p = q_p \,.\, A_t$$

CONE PENETRATION VERSUS PILE



Due to similarity between cone and pile, the cone can be considered as a simple mini pile.

- f_s can be correlated to f,
- q_c can be correlated to q_p



ESTIMATION OF PILE CAPACITY FROM CPT DATA

- **Indirect Approach**

  – **Use the CPT data (q_c, f_s) to evaluate the soil strength parameters strength parameters, such as undrained shear strength (S_u) for clay and angle of internal friction (ϕ) for sand, from CPT data → input for Static Analysis Methods.**

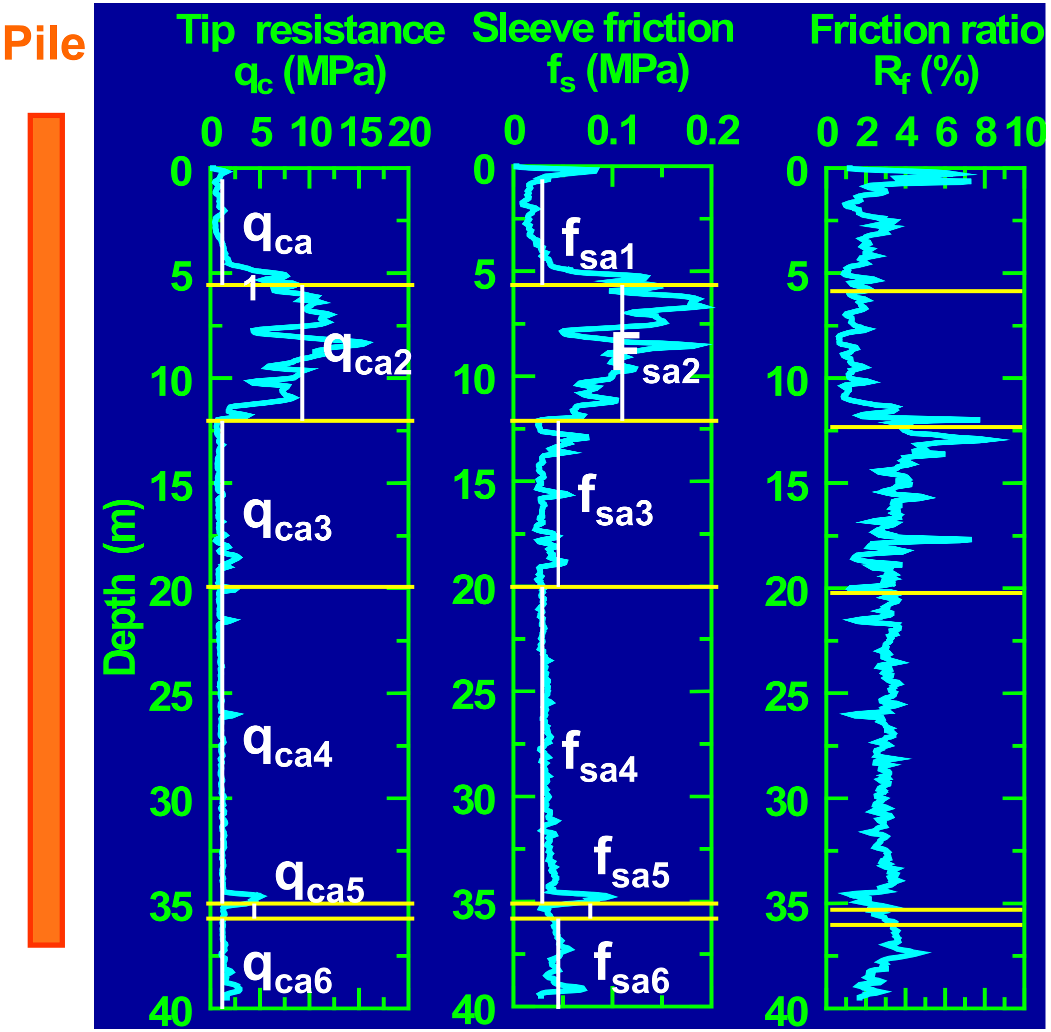
- **Direct Approach ✓**

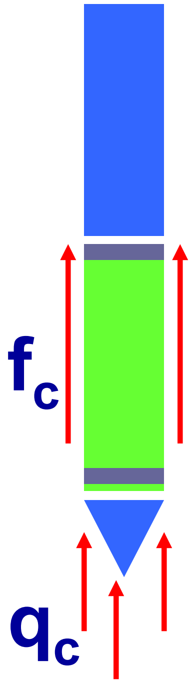
  Evaluate pile capacity directly from CPT data (q_c, f_s)

  – **The pile unit toe resistance (q_p) is evaluated from the cone tip resistance (q_c) profile,**

  – **The pile unit shaft resistance (f) is evaluated either from the sleeve friction (f_s) or from the cone tip resistance (q_c) profiles.**

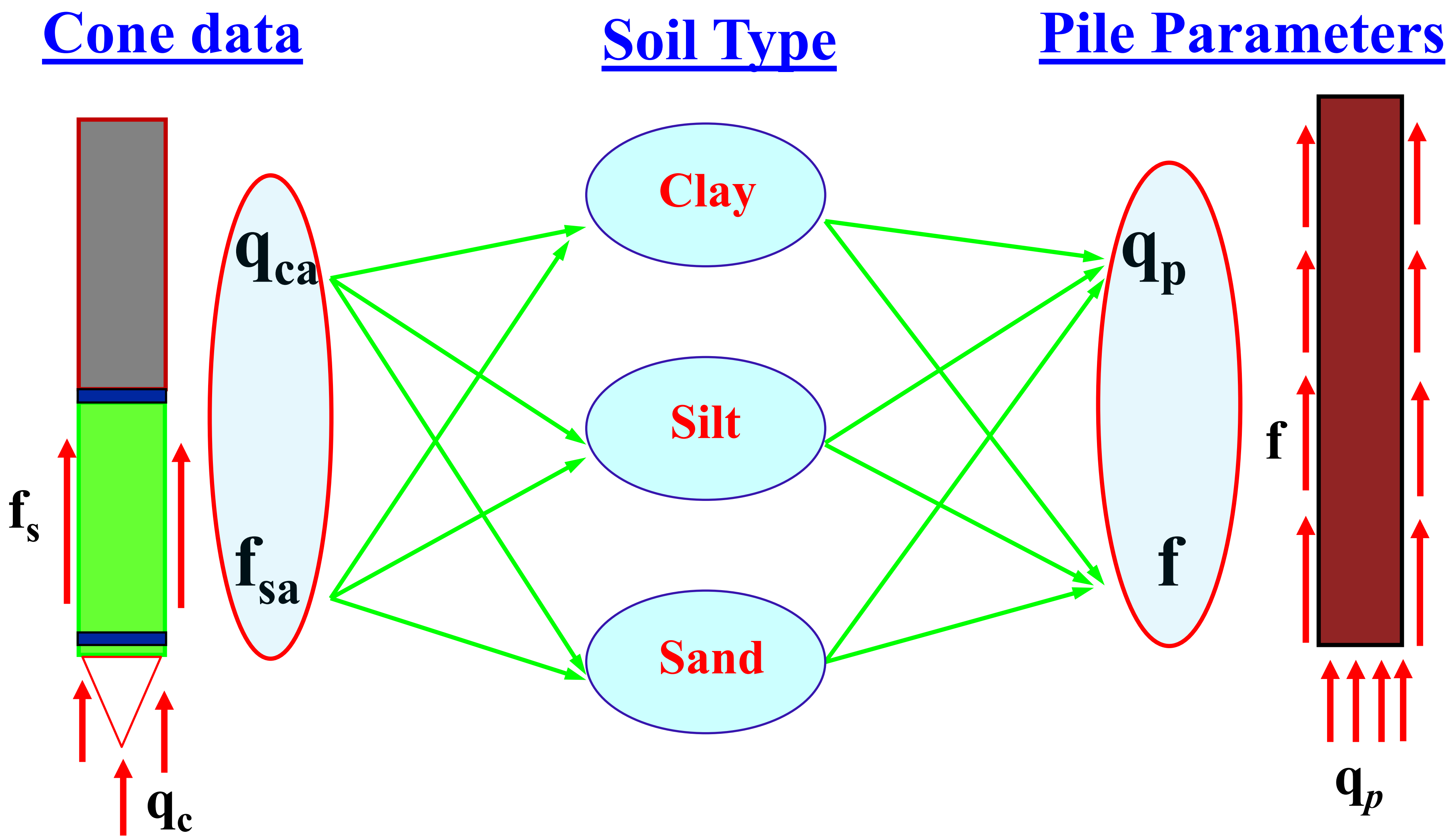
ESTIMATION OF PILE CAPACITY FROM CPT





$$R_f = \frac{f_c}{q_c} \,.\, 100\%$$

ESTIMATION OF PILE CAPACITY FROM CPT DATA



DIRECT PILE-CPT DESIGN METHODS

1- Schmertmann
2- De Ruiter and Beringen
3- LCPC (Bustamante and Gianeselli)
4- Tumay and Fakhroo
5- Aoki and De Alencar
6- Price and Wardle
7- Philipponnat
8- Penpile
9- NGI
10- ICP
11- UWA
12- CPT2000
13- Fugro
14- Purdue
15- Probabilistic
16- UF
17- Togliani
18- Zhou
19- ERTC3
20- German
21- Eurocode

EXAMPLE: UF CPT METHOD

➢ The unit end bearing capacity:

$$\boxed{q_t = k_b q_{ca} \quad < 150\ \text{TSF}}$$

$$q_{ca} = \frac{q_{c1} + q_{c2}}{2}$$

Soil Type	k_b
Well cemented sand	0.1
Lightly cemented sand	0.15
Gravel	0.35
Sand	0.40
Silt	0.45
Clay	1.0

q_{c1}: average cone tip resistance within 3b (b is the pile width) below the pile tip; q_{c2}: average cone tip resistance within 8b (b is the pile width) above pile tip.

In cases that $q_{c2} > q_{c1} \rightarrow \quad q_{c2} = q_{c1}$

➢ The unit side capacity:

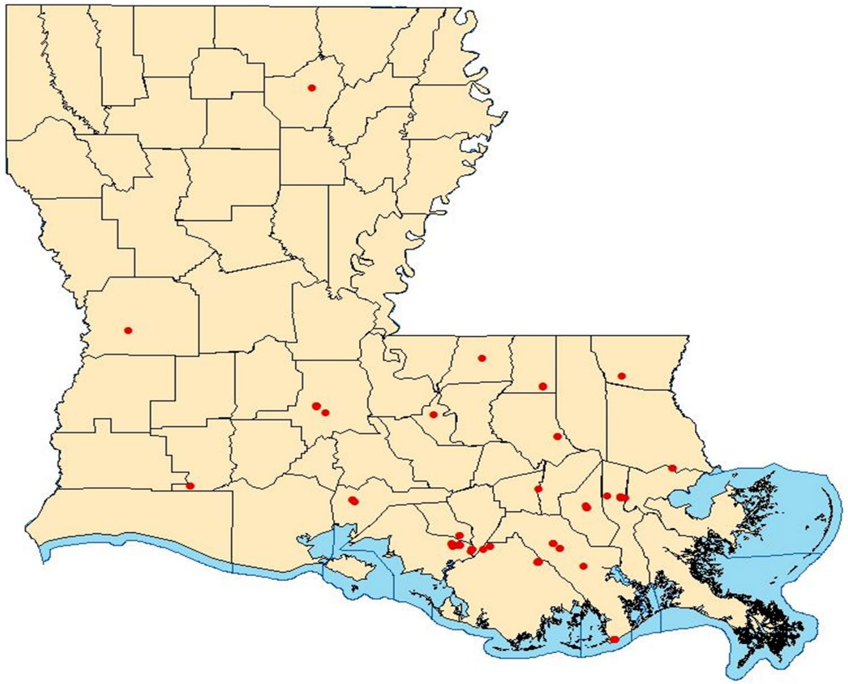
$$\boxed{f_{si} = q_{ci(side)} \frac{\alpha_s}{F_s} < 1.2TSF}$$

α_s: depends on the pile type (α_s equals to 1.25 for precast concrete driven piles)

Soil Type	Fs
Clay and calcareous clay	50
Silt, sandy clay, and clayey sand	60
Loose sand	100
Medium dense sand	150
Dense sand and gravel	200

PILE LOAD TEST DATABASE

- The database consists of eighty (80) precast prestressed concrete (PPC) piles of different sizes and lengths were collected from 34 different project sites across the state of Louisiana.
- All the piles were square piles loaded to failure under static load tests. The corresponding CPT tests were conducted close to each test pile. The pile lengths range from 36 ft. to 200 ft., and the pile widths range from 14 in. to 36 in.
- The pile load tests were performed based on quick load test as described by ASTM D1143 testing procedure. The tests were performed 14 days after pile driving , partially accounted for pile setup.
- Davisson interpretation criteria was used to estimate the ultimate pile capacity from the load-settlement curve for each pile load test.



DEVELOPMENT OF NEURAL NETWORK MODEL

Model Input Parameters

- The proper selection of input variables is very important for developing ANN models, since it has significant impact on the performance of the ANN models.
- Based on prior knowledge from literature, the selected input variables were: *pile embedment length, L, pile width, B, corrected cone tip resistance, q_t, and cone sleeve friction, f_s.* The ultimate pile capacity, q_t, was the only output.
- There are some other factors, such as the pile installation method, pile type, whether the pile tip is open or closed, shape of pile cross-section, etc. These factors were ignored in this study since all the tested piles were square precast prestressed concrete (PPC) driven pile with closed tip.

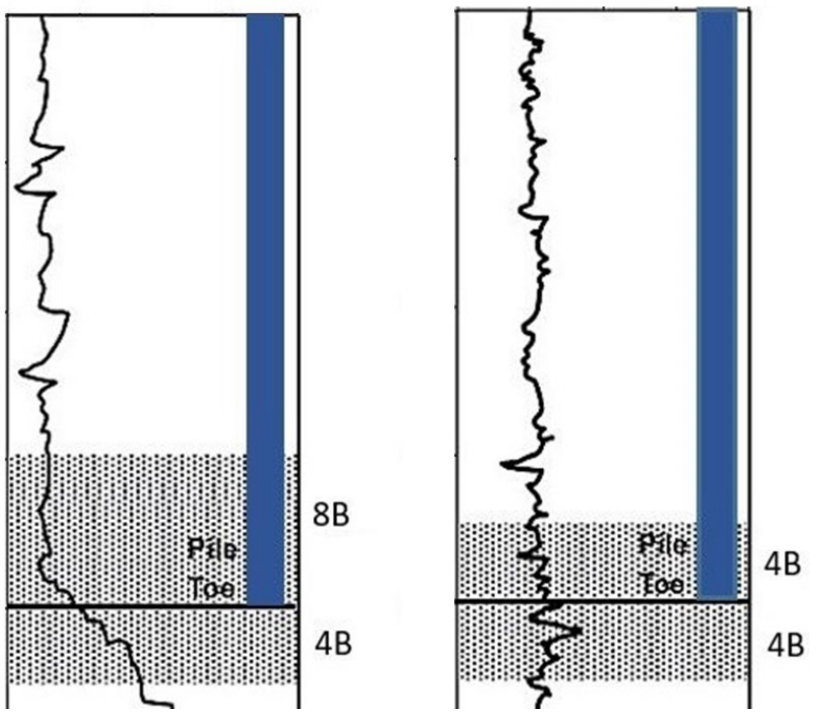
DEVELOPMENT OF NEURAL NETWORK MODEL

Model Input Parameters

- The soil properties along the shaft of the pile varies with depth.
- To account for this variability, the embedded length of the piles was divided into five equal segments (layers). For each division, the average $q_{t,\,avg}$ and $f_{s,avg}$ were determined as follow:

$$q_{t,\,avg} = \frac{\sum q_{ti}\, Z_i}{\sum Z_i}\ , \qquad f_{s,\,avg} = \frac{\sum f_{si}\, Z_i}{\sum Z_i}$$

- For calculating the pile end bearing capacity, the average corrected tip resistance, $q_{t\text{-}tip}$, was calculated for two cases of influence zone: 4B below to 4B above pile toe, and 4B below to 8B above pile toe, in order to find the best results.



DEVELOPMENT OF NEURAL NETWORK MODEL

Model Input Parameters

- The final selection of ANN input parameters were: (1) Pile embedment depth, L, (2) Pile width, B, (3) $q_{t,\ avg\ 1}$, (4) $q_{t,\ avg\ 2}$, (5) $q_{t,\ avg\ 3}$, (6) $q_{t,\ avg\ 4}$, (7) $q_{t,\ avg\ 5}$, (8) $f_{s,\ avg\ 1}$, (9) $f_{s,\ avg\ 2}$, (10) $f_{s,\ avg\ 3}$, (11) $f_{s,\ avg\ 4}$, (12) $f_{s,\ avg\ 5}$, (13) $q_{t\text{-}tip,\ 4B/8B\ above}$, (14) $q_{t\text{-}tip,\ 4B\ below}$.
- These inputs parameters were arranged in six different combinations (6 ANN Model Types) to determine the ANN model(s) that yields the best performance in terms of estimating the measured ultimate pile capacity of driven PPC piles.

DEVELOPMENT OF NEURAL NETWORK MODEL

Sample of Data Set

Width (in)	L (ft)	$q_{t,avg1}$ (tsf)	$q_{t,avg2}$ (tsf)	$q_{t,avg3}$ (tsf)	$q_{t,avg4}$ (tsf)	$q_{t,avg5}$ (tsf)	$q_{t\text{-tip}, \text{8B above}}$ (tsf)	$q_{t\text{-tip, 4B above}}$ (tsf)	$q_{t\text{-tip}, \text{4B below}}$ (tsf)	$f_{s,avg1}$ (tsf)	$f_{s,avg2}$ (tsf)	$f_{s,avg3}$ (tsf)	$f_{s,avg4}$ (tsf)	$f_{s,avg5}$ (tsf)	Q_u (tons)
24	54.2	27.60	23.5	46.9	17.8	11.3	11.75	11.94	10.48	1.45	0.88	1.12	1.05	0.32	265
24	49.1	19.34	23.8	26.3	28.5	17.8	32.65	22.44	17.82	0.78	1.00	1.05	0.95	0.77	239
30	86	24.66	29.1	27.5	32.7	47.9	41.33	72.42	27.43	1.09	1.24	1.03	0.69	0.96	570
24	61	27.20	25.2	34.3	46.6	19.8	37.38	50.78	19.31	0.82	0.74	1.31	0.78	0.70	275
24	85	9.68	11.3	7.36	10.0	18.9	12.61	17.78	20.17	0.42	0.35	0.31	0.32	0.46	205
14	63.7	8.51	6.28	5.67	29.1	55.7	56.53	45.43	44.88	0.25	0.21	0.17	0.24	0.63	127
24	87	11.90	11.8	15.8	36.6	28.3	47.33	24.58	31.82	0.46	0.42	0.38	0.50	0.58	309
30	72.5	50.16	46.8	42.2	69.8	58.2	87.63	50.03	60.11	0.12	0.38	0.58	0.45	0.45	374
24	60	51.51	259.	196.	75.9	40.5	92.39	38.14	42.94	0.45	1.32	1.41	1.18	0.92	210
24	39	18.77	1.50	3.16	4.30	6.67	4.02	3.26	8.21	0.71	0.21	0.12	0.16	0.17	66
…	…	…	…	…	….	…	….	….	….	….	….	….	….	…..	….

1

DEVELOPMENT OF NEURAL NETWORK MODEL

Types of ANN Models

Types of ANN Model	Input Parameters
Type 1	(1) Pile embedment depth, L, (2) Pile width, D, (3) $q_{t, avg 1}$, (4) $q_{t, avg 2}$, (5) $q_{t, avg 3}$, (6) $q_{t, avg 4}$, (7) $q_{t, avg 5}$, (8) $q_{t\text{-}tip, 4B above}$, (9) $q_{t\text{-}tip, 4B below}$
Type 2	(1) Pile embedment depth, L, (2) Pile width, D, (3) $q_{t, avg 1}$, (4) $q_{t, avg 2}$, (5) $q_{t, avg 3}$, (6) $q_{t, avg 4}$, (7) $q_{t, avg 5}$, (8) $q_{t\text{-}tip, 8B above}$, (9) $q_{t\text{-}tip, 4B below}$
Type 3	(1) Pile embedment depth, L, (2) Pile width, D (3) $f_{s, avg 1}$, (4) $f_{s, avg 2}$, (5) $f_{s, avg 3}$, (6) $f_{s, avg 4}$, (7) $f_{s, avg 5}$, (8) $q_{t\text{-}tip, 4B above}$, (9) $q_{t\text{-}tip, 4B below}$
Type 4	(1) Pile embedment depth, L, (2) Pile width, D (3) $f_{s, avg 1}$, (4) $f_{s, avg 2}$, (5) $f_{s, avg 3}$, (6) $f_{s, avg 4}$, (7) $f_{s, avg 5}$, (8) $q_{t\text{-}tip, 8B above}$, (9) $q_{t\text{-}tip, 4B below}$
Type 5	(1) Pile embedment depth, L, (2) Pile width, D, (3) $q_{t, avg 1}$, (4) $q_{t, avg 2}$, (5) $q_{t, avg 3}$, (6) $q_{t, avg 4}$, (7) $q_{t, avg 5}$, (8) $f_{s, avg 1}$, (9) $f_{s, avg 2}$, (10) $f_{s, avg 3}$, (11) $f_{s, avg 4}$, (12) $f_{s, avg 5}$, (13) $q_{t\text{-}tip, 4B above}$, (14) $q_{t\text{-}tip, 4B below}$
Type 6	(1) Pile embedment depth, L, (2) Pile width, D, (3) $q_{t, avg 1}$, (4) $q_{t, avg 2}$, (5) $q_{t, avg 3}$, (6) $q_{t, avg 4}$, (7) $q_{t, avg 5}$, (8) $f_{s, avg 1}$, (9) $f_{s, avg 2}$, (10) $f_{s, avg 3}$, (11) $f_{s, avg 4}$, (12) $f_{s, avg 5}$, (13) $q_{t\text{-}tip, 8B above}$, (14) $q_{t\text{-}tip, 4B below}$

DEVELOPMENT OF NEURAL NETWORK MODEL

Training of ANN Models

- Training of ANN model refers to the process of initializing a network through the deployment of initial values and then optimizing the connection weights in order to obtain global minima instead of a local one.
- A widely used method to obtain the optimum weights is the back-propagation algorithm or the gradient descent method. However, the convergence is sometimes slower and requires lots of iterations. Therefore, a faster Quasi-Newton method was used in this work to optimize weights for the ANN model.

Stopping Criteria of Training Process

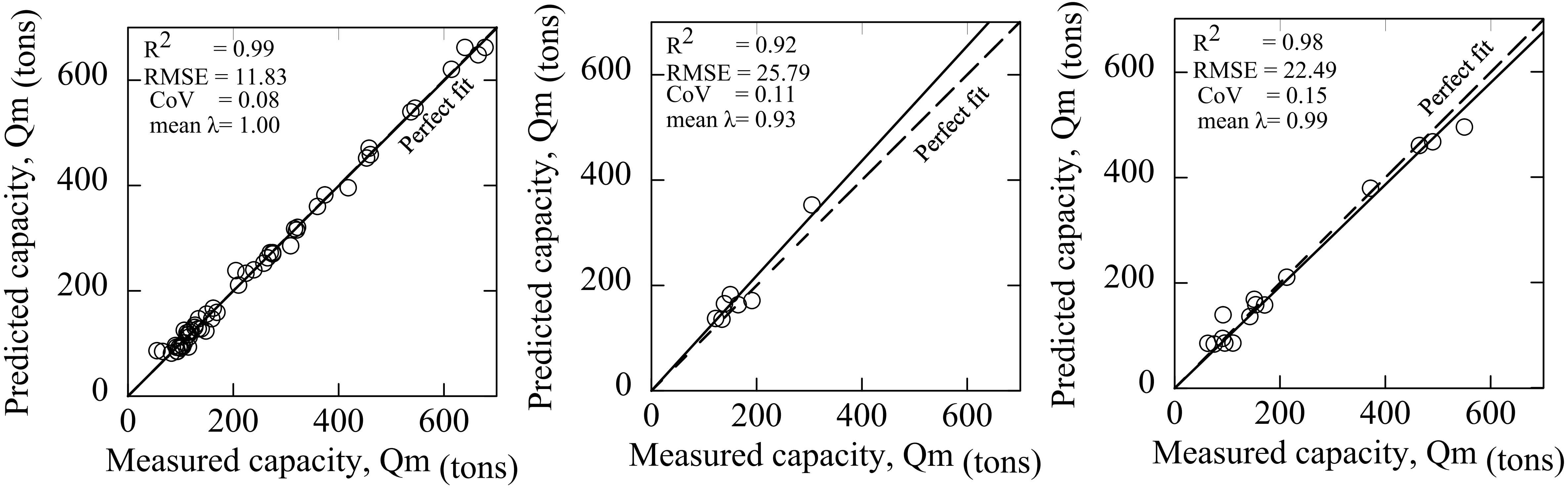
- It is important to determine when to stop the training process. In this study, the cross-validation method was implemented where data was divided into three sets: 70% training, 12% testing and 18% validation.
- The function of training set is to re-adjust the connection weights. The testing set judges the capability of the model to be generalized, through evaluating the performance of the model at different stages of the training process. When an increase in error is detected, the training process is stopped. The validation set ensures the model's ability to be generalized in a robust way within the limits of training data.

RESULTS OF ANN MODELS

ANN type	ANN model	Phase	*r*	R^2	RMSE (tons)	Mean λ_R	COV
Type 1	9-7-1	Training	0.99	0.97	28.45	1.00	0.18
		Testing	0.98	0.90	52.09	0.94	0.20
		validation	0.98	0.93	25.39	0.93	0.17
Type 2	9-7-5-1	Training	0.98	0.97	27.42	1.00	0.18
		Testing	0.95	0.90	35.46	1.14	0.23
		validation	0.97	0.91	29.40	0.97	0.20
Type 3	9-7-7-1	Training	0.99	0.99	11.65	1.00	0.08
		Testing	0.94	0.68	33.23	1.06	0.19
		validation	0.99	0.98	26.78	0.99	0.19
Type 4	9-7-7-1	Training	0.99	0.99	11.83	1.00	0.08
		Testing	0.96	0.92	25.79	0.93	0.11
		validation	0.99	0.98	22.49	0.99	0.15
Type 5	14-9-3-1	Training	0.99	0.99	10.18	1.00	0.08
		Testing	0.98	0.94	14.78	0.96	0.08
		validation	0.99	0.97	24.90	0.96	0.14
Type 6	14-9-4-1	Training	0.99	0.99	7.17	1.00	0.07
		Testing	0.97	0.94	30.27	0.96	0.23
		validation	0.99	0.98	29.65	0.97	0.14

- The performance of ANN model was evaluated based on the coefficient of correlation, r, coefficient of determination, R^2, root mean of squared errors, RMSE, mean bias factor, λ, and the coefficient of variation, COV.
- The ANN models are designated in a manner to understand its structure. For example, for the model designated as 9-4-1-1, the first and last number refers to the number of nodes in the input and output layers, respectively. The intermediate numbers denote the number of hidden layers and nodes.

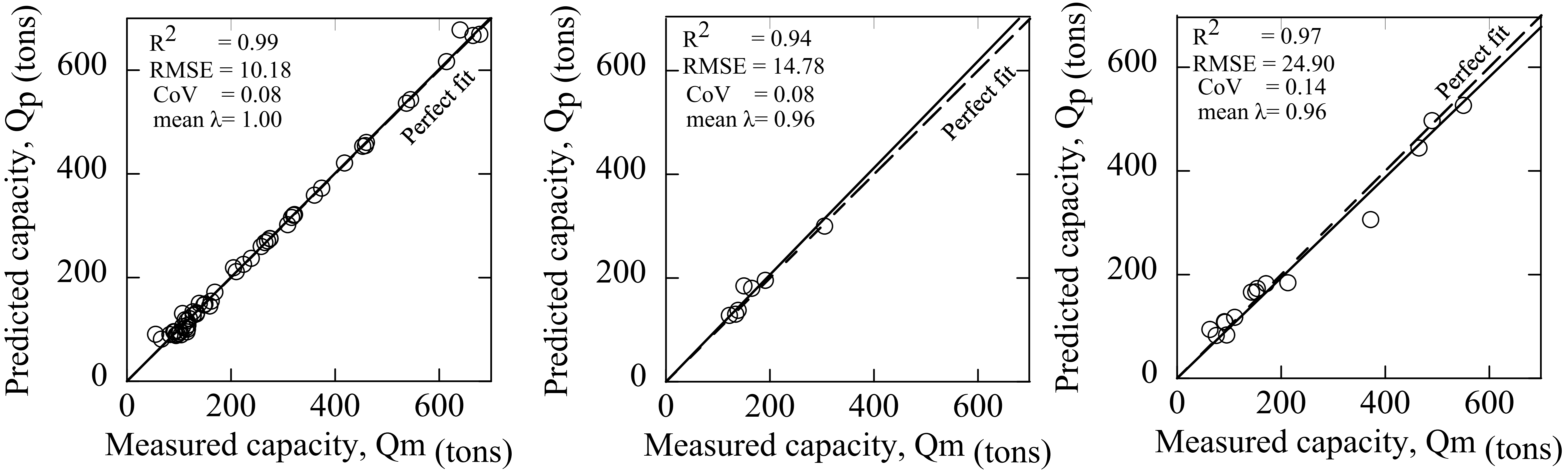
RESULTS OF ANN MODELS: TYPE 4 ANN MODEL 9-7-7-1



Training (70%) **Testing (12%)** **Validation (18%)**

Data for each case was selected randomly

RESULTS OF ANN MODELS: TYPE 5 ANN MODEL 14-9-3-1



Training (70%) **Testing (12%)** **Validation (18%)**

Data for each case was selected randomly

SENSITIVITY ANALYSIS (14-9-3-1)

CPT Input Variables	The Relative Importance of the Input Variables (%)
Embedment length of pile, L	14.8
Width of pile, B	14.1
$q_{t\text{-tip, 4B above}}$	19.0
$q_{t\text{-tip, 4B below}}$	22.8
$q_{t\text{-avg}}$ along the pile shaft	12.9
$f_{s\text{-avg}}$ along the pile shaft	16.4

COMPARISON WITH TRADITIONAL PILE-CPT METHODS

- Amirmojahedi and Abu-Farsakh (2019) evaluated 21 traditional direct pile-CPT methods for estimating the ultimate pile capacity form CPT data (q_t,f_s) using a database of 80 pile load tests, and ranked LCPC, probabilistic and UF methods as the best three performed pile-CPT methods.
- The best-performed ANN models (9-7-7-1, 14-9-3-1) developed in this study were compared with the aforementioned three pile-CPT methods.
- The comparison clearly shows that, the ANN models outperform these three pile-CPT methods in almost all evaluation criteria. Especially the RMSE value seems to be much higher in the conventional methods.

Method	Q_{fit}/Q_m	R^2	RMSE (Tons)	Mean λ	COV
LCPC	1.10	0.91	57.13	0.96	0.27
Probabilistic	0.99	0.91	35.29	0.97	0.21
UF	1.12	0.93	51.30	0.99	0.25
ANN (9-7-7-1)	0.97	0.98	22.49	0.99	0.15
ANN (14-9-3-1)	0.97	0.97	24.90	0.96	0.14

EVALUATION AND COMPARISON BASED ON LRFD ANALYSIS

- LRFD analysis help to grasp a better understanding of efficiency of the developed ANN models.
- First Order Reliability Method (FORM) was used to calibrate the LRFD resistance factors.
- Q_D/Q_L equal to 3 (specified by AASHTO LRFD)
- A target reliability (β_T) of 2.33 was selected

Pile Capacity Method	Data Set	Bias, λ_R	COV	Resistance Factor, ϕ	Efficiency ϕ/λ_R
LCPC	Whole data set (80 piles)	1.04	0.31	0.60	0.57
Probabilistic		1.08	0.34	0.57	0.53
UF		1.05	0.27	0.65	0.62
ANN (9-7-7-1)		0.99	0.107	0.88	0.88
ANN (14-9-3-1)		0.99	0.10	0.89	0.90
ANN (9-7-7-1)	Validation data set (16 piles)	0.97	0.15	0.79	0.81
ANN (14-9-3-1)		0.97	0.14	0.81	0.83

Bias factor, $\lambda_R = \frac{Q_m}{Q_p}$

LIMITATIONS OF STUDY

- The data set represents clayey soils in Louisiana. Thus, the proposed ANN models should perform well for clayey soils in Louisiana, and other locations with similar geological conditions.
- The range of q_t should be (0-300) tsf, the range of f_s should be (0-3.2) tsf and B should be $\leq$36 in, and the range of Qt should be (0-678) tons.
- Recommended for squared PPC driven piles only.
- The developed ANN models should be used to predict the data for unknown sites without further training. If it is trained again on the same training data, the prediction capability might not remain the same.

CONCLUSIONS

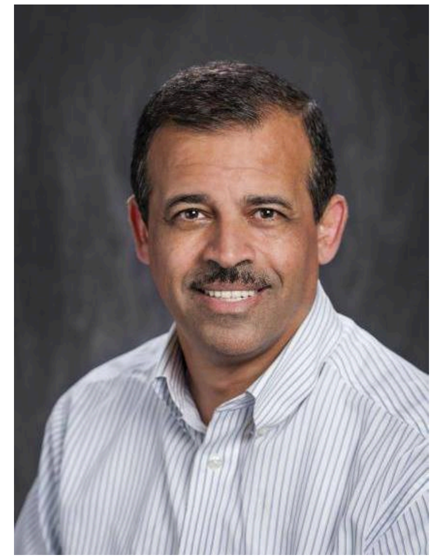
- All the developed ANN model types were able to estimate the measured ultimate capacity of the 80 pile load tests with good to excellent accuracy.
- However, Type 4 ANN model 9-7-7-1 ($\lambda = 0.99$, RMSE = 22.49, COV = 0.15) and Type 5 ANN model 14-9-3-1 ($\lambda_{av} = 0.96$, $RMSE_{av} = 21.53$, $COV_{av} = 0.12$) showed better performance.
- Using the combination of $q_{t,\ avg}$, and $f_{s,\ avg}$, to evaluate the pile's skin friction gives better ANN prediction models.
- Sensitivity analysis showed that the $q_{t\text{-tip},4B\ below}$, has relatively the highest importance input parameter.
- $f_{s\text{-avg}}$, has higher importance than $q_{t\text{-avg}}$ along the shaft in evaluating pile skin friction.

CONCLUSIONS

- The comparison with LCPC, probabilistic, and UF methods clearly showed that the ANN models outperformed the traditional pile-CPT methods with lower RMSE and lower COV.
- The evaluation and comparison based on LRFD reliability analysis demonstrated higher resistant factors and superior efficiencies for the ANN models.
- Finally, the ANN models use data and previous experience and training without incorporating any assumption or hypothesis. Besides, the ANN models can be continuously updated with time to achieve more accurate estimation results, whenever new pile load test data are available.

THANK YOU!!

Today’s Panelists



Moderated by:
Sharid Amiri,
California DOT

Nick Machairas,
Haley & Aldrich

Murad Abu-Farsakh,
Louisiana State University

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