

Organization and Analysis of Measurement While Drilling (MWD) Data

Final Presentation

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MONTANA
TECHNOLOGICAL UNIVERSITY



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Quick Summary

• What is MWD?

- Instrumented drill rig:
 - Job and measure time
 - Depth
 - Drilling rate
 - Down pressure
 - Rotation speed
 - Rotation torque
 - Tool acceleration
 - Fluid flow rate
 - Fluid injection pressure

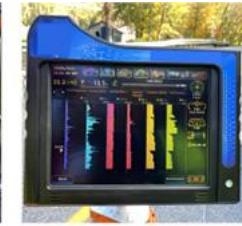
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• Why?

- Accurate geological profiling
- Geotechnical parameters
- Detection of voids, fissures, other anomalies
- Potential increase in productivity by reducing the number of time-consuming Standard Penetration Test (SPT) profiles
- Overall control of the drilling process



a. Junction Box



b. Data Logger



c. Driller's Button



d. Thrust Pressure Sensor



e. Water Pressure Sensor



f. (I) Torque and (II) Vibration Sensors



g. Rotation Sensor



h. Flow Meter



i. Depth Sensor

Geostrata, Dec 23/Jan 24, Benoit & Souza

- Who's using it?

- More than a dozen agencies and organizations across the U.S. have instrumented drill rigs
 - 11 state DOT's
 - 2 federal agencies
- Europe
 - Longer history of MWD use
 - Hollow stem auger (HSA) drilling more common in U.S. – high torque, mechanically driven rigs
 - Hydraulic drill rigs more common in Europe



Geostrata, Dec 23/Jan 24, Lindenbach et al.

MWD in Montana

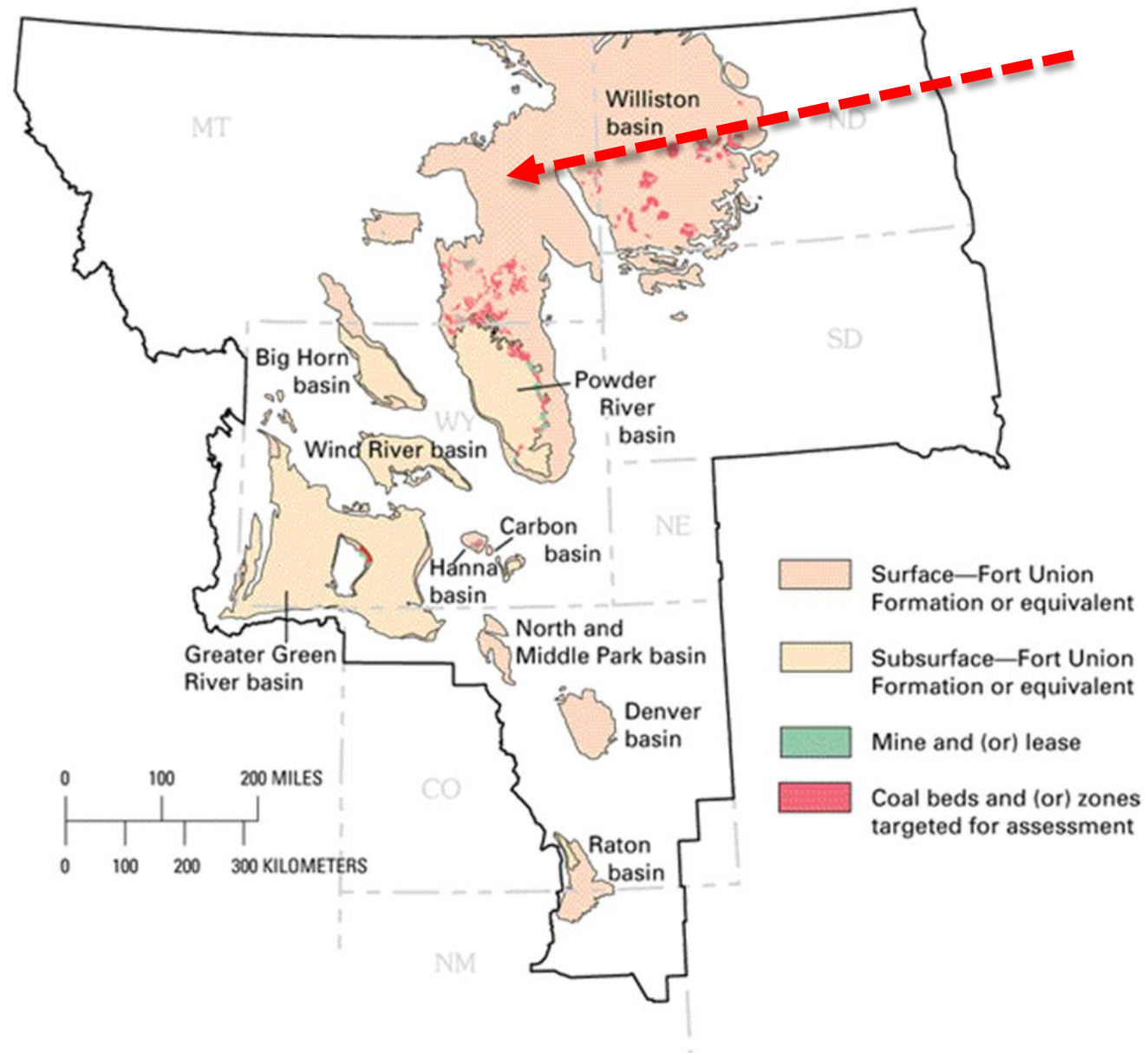
- Eastern Montana fine grained soils and IGM's (Intermediate GeoMaterials)
- Sedimentary rocks - Fort Union Formation
- Unconfined compressive strength (UCS) less than 725 psi
- International Society for Rock Mechanics:
 - Extremely weak rock 35 to 150 psi
 - Very weak rock 150 to 725 psi

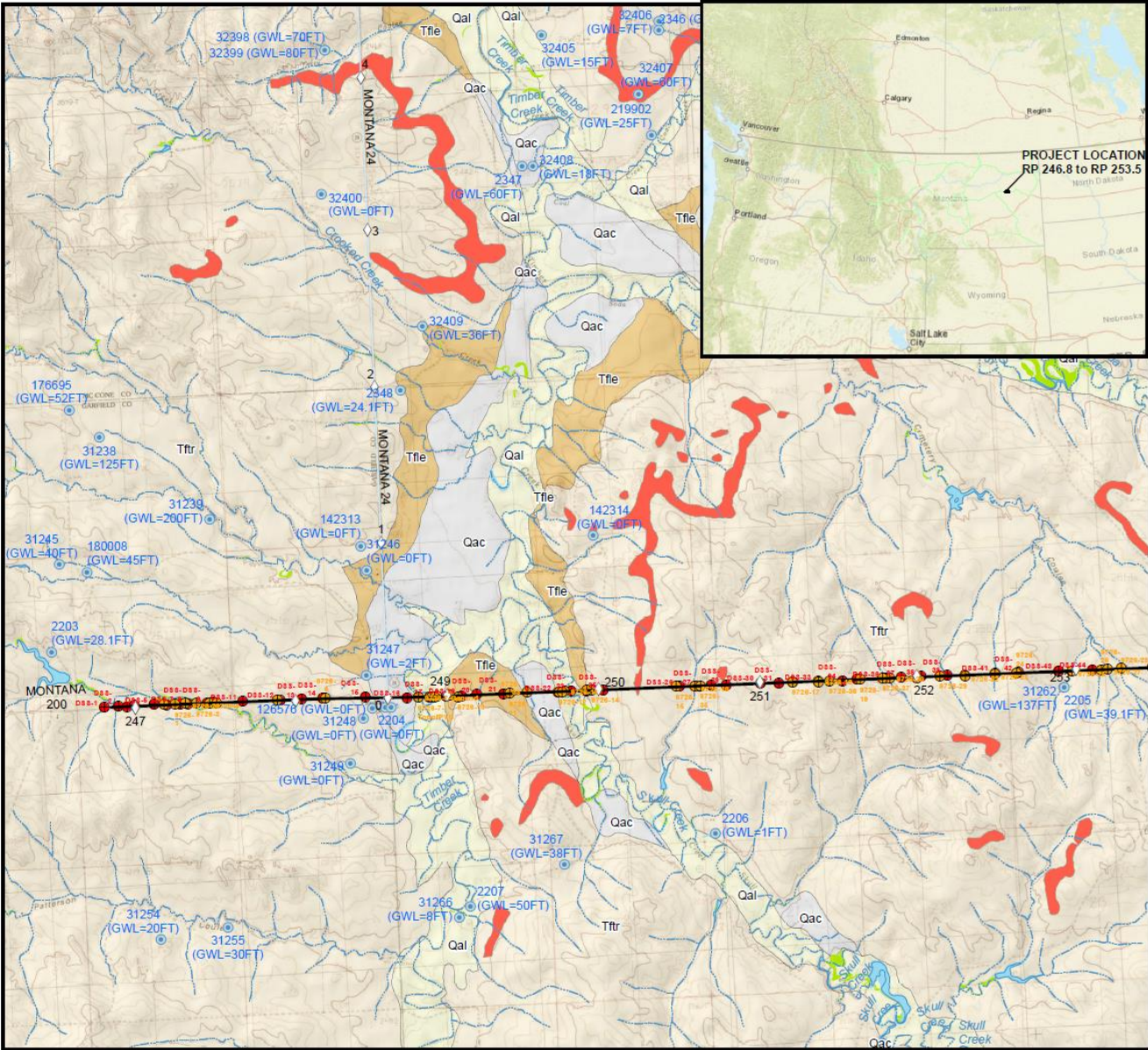
Jean Lutz Sensors

- Dialog MX
- Depth Sensor
- RPM Sensor
- Down Pressure & Clamp Sensors
- Vibration Sensor
- Flow Rate & Injection Sensors



Montana Department of Transportation

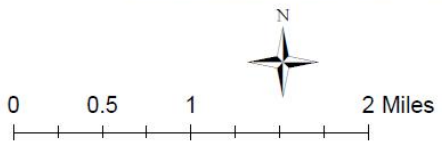
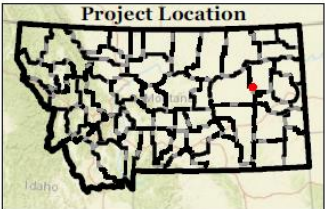


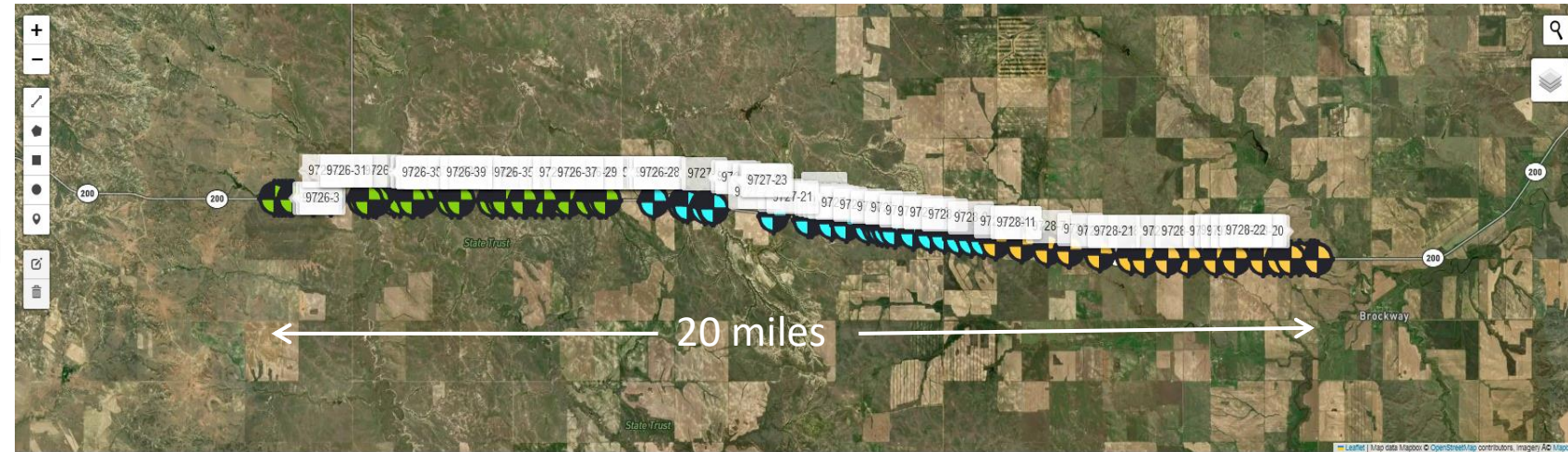


Area Geology:
The surficial geology through the project length traverses predominantly the Tongue River Member of the Fort Union Formation (Tftr), which is characterized by fine to medium-grained yellowish-brown to orangish-brown or tan sandstone with thinner interbeds of light yellowish-brown to orangish-brown or tan siltstone and light-colored mudstone and claystone and brownish-gray carbonaceous shale and coal. Quaternary alluvium and colluvium (Qac and Qal) are found as the highway crosses the Timber Creek & Skull Creek drainages.

The Lebo Member of the Fort Union Formation (Tfle) outcrops between the two drainages and consists of gray to greenish-gray smectitic shale and mudstone with lenses and interbeds of gray to yellow, very fine to medium grained poorly resistant sandstone. Beds of very localized clinker (QTcl) are mapped within the extents of the project and may be encountered within road cuts during construction of the project.

Based on well logs near the site, obtained from the Montana Bureau of Mines and Geology (MBMG) Ground Water Information Center (GWIC), artesian groundwater conditions may be encountered in the vicinity of the Flowing Wells rest area. Static groundwater levels (GWL) exceed 30 feet below the ground surface through the remainder of the project extents.





Filter Data Export Data 82 visible features

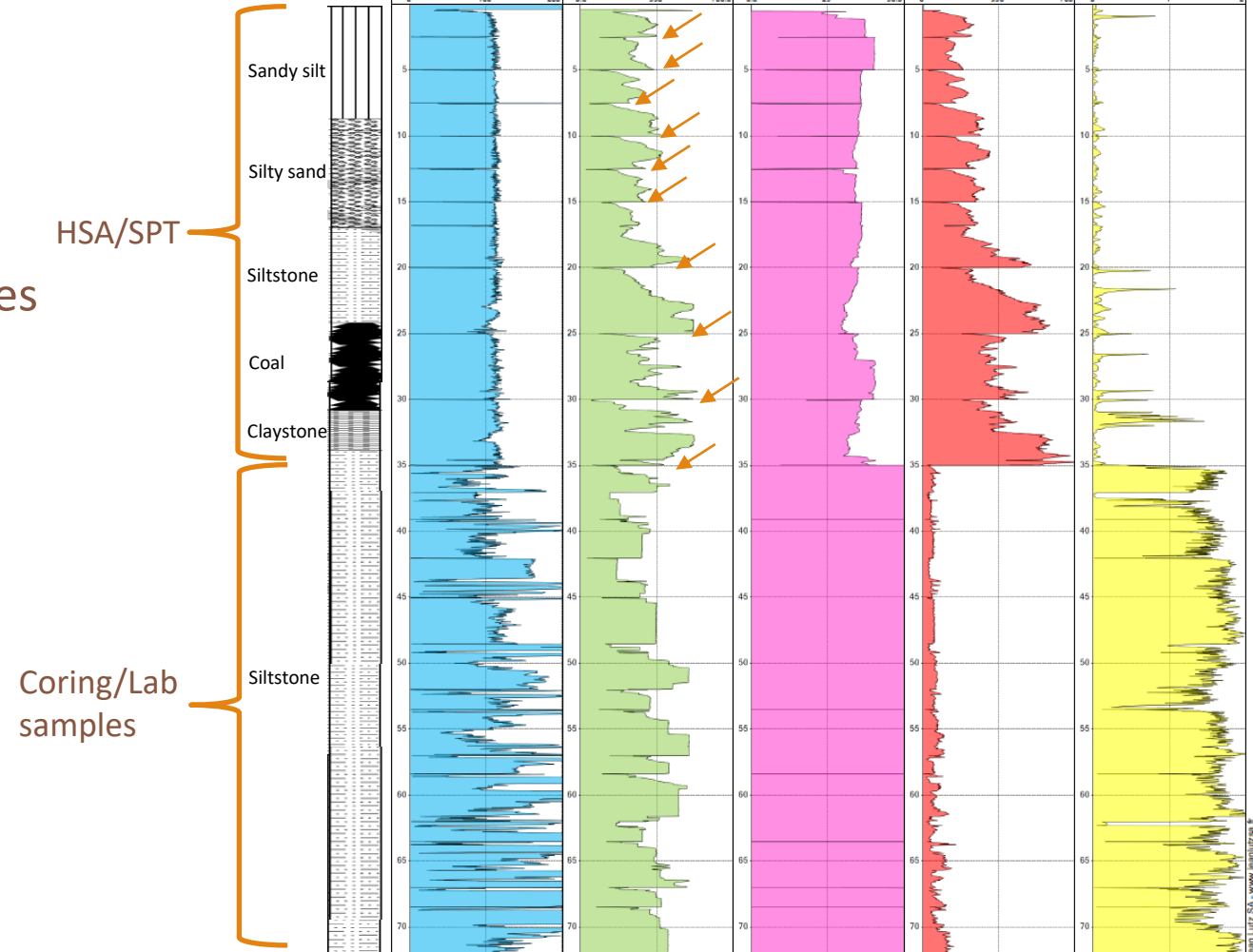
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Q i	9727-6	MWD	SPT, MWD		
Q i	9727-5	MWD	SPT, MWD, VST, UCS	MWD_Research/9727000/9727-5	Point Files
Q i	9727-4	MWD	SPT, MWD, VST	MWD_Research/9727000/9727-4	Point Files
Q i	9727-3	MWD	SPT, MWD		
Q i	9727-23	MWD	CSPT (1.875" DIA SPOON), MWD, VST, PMT, BST, UCS	MWD_Research/9727000/9727-23	Point Files
Q i	9727-22	MWD	CSPT (1.875" DIA SPOON), MWD, VST, PMT, BST, UCS	MWD_Research/9727000/9727-22	Point Files
Q i	9727-21	MWD	SPT, MWD		
Q i	9727-20	MWD	SPT, MWD		
Q i	9727-2	MWD	SPT, MWD		

- MWD:
 - *HSA: 0 to ~ 25 to 30 feet
 - SPT over HSA interval
 - Coring with fluid below HSA
- Data preparation
 - SPT data parsing (see arrows)
 - Analysis targets:
 - SPT blows per foot at HSA auger changes
 - UCS/Unit weight from coring/lab data

*HSA – Hollow Stem Auger



9727-7



Project	Job No	Owner	Area	Data Type	Location
West of Brockway-West	9727			MWD-LUTZ	
RigID	Date	Total Depth	Operator		Water Table (feet)
1050	[1x1 datetime]	72.02	Duncan		0.00



Analysis data

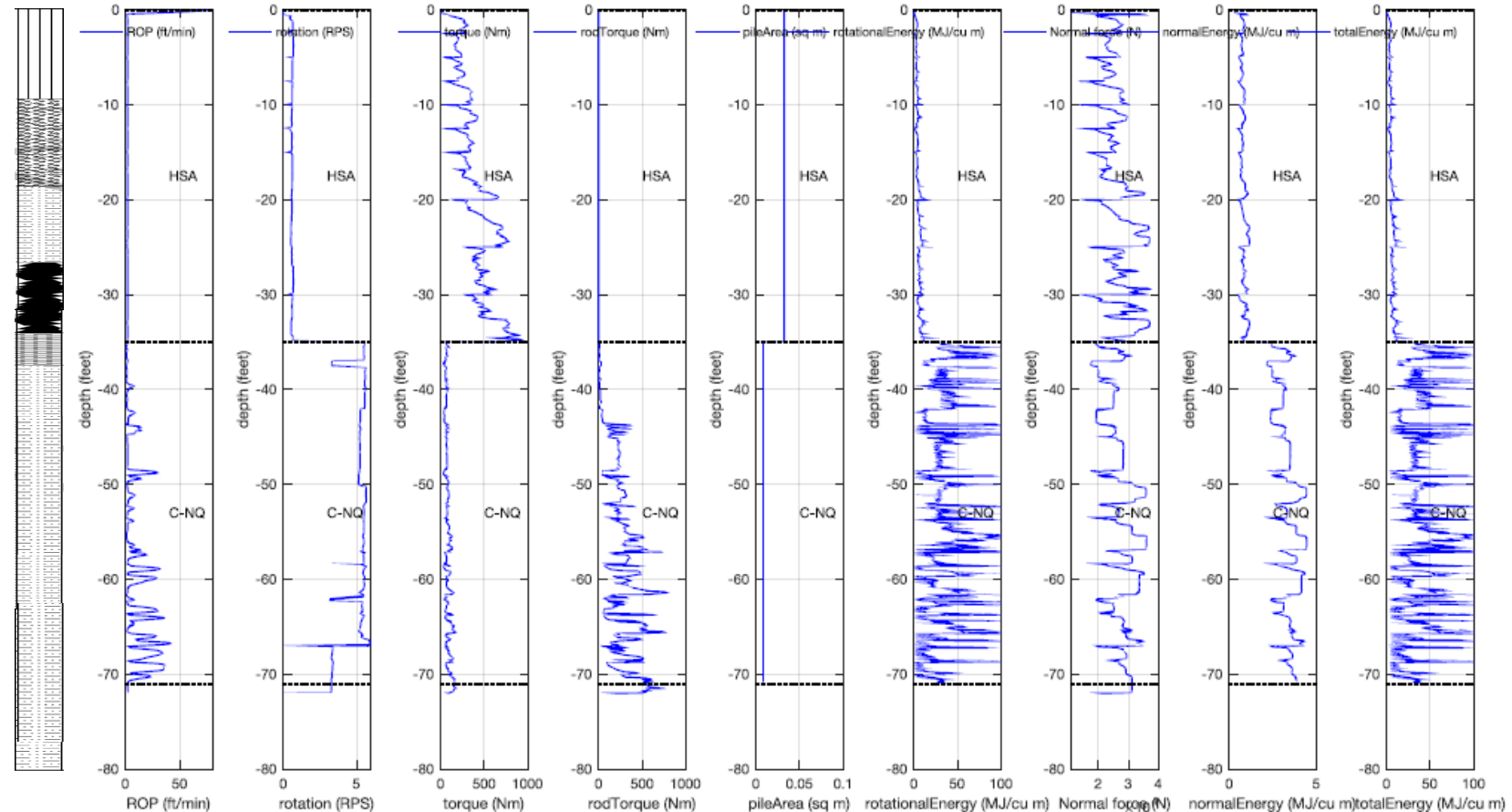
Input data:

- Depth (ft)
- Peak down pressure (psi)
- Rotation torque (lb-ft)
- Rotation speed (rev/min)
- Moving speed (ft/h)
- *Specific energy (ft-lb/ft³)

*compound parameter

Prediction targets:

- SPT blow counts/foot
- UCS
- Unit Weight



Northing (feet)	Easting (feet)	Elevation (feet)	Latitude (deg)	Longitude (deg)	Tip Elevation (feet)
1138962.40	2838604.42	2650.75	47.796389	106.779167	2578.73
Created on: 04/24/2023 10:55			Filename: 9727-07_MWD_drillCode.mat_c0185927c3063bdbc679a5764227190		
Comments:					

Compound parameters: specific/drilling energies and Somerton index

$$\text{Somerton index} = \frac{P}{\sqrt{V}}$$

$$\text{Specific drilling energy} = \frac{F}{A} + \frac{2\pi NT}{AV}$$

$$\text{Drilling energy} = \frac{TN}{V}$$

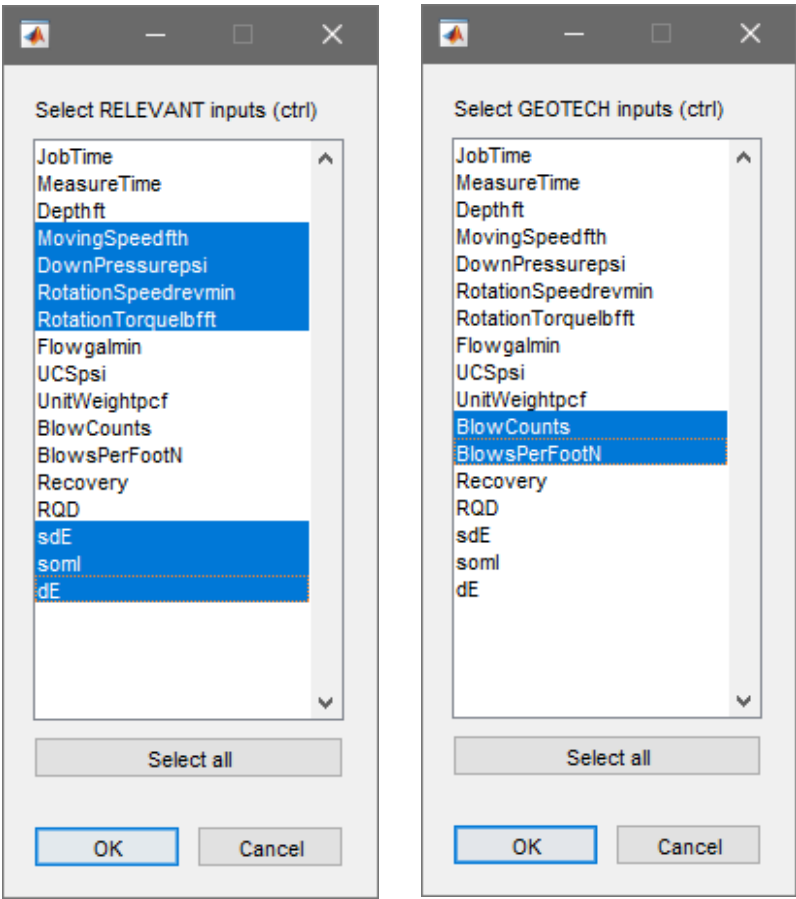
Source: Guidelines on Measurement While Drilling (MWD) for Geotechnical Investigations

Used by various researchers in varying situations

Used for our analysis

- $\frac{F}{A} = P = \text{down pressure}$
- $N = \text{rotation rate}$
- $T = \text{torque}$
- $A = \text{area}$
- $V = \text{penetration rate}$
- $R = \text{rotation rate}$

Matlab user interface

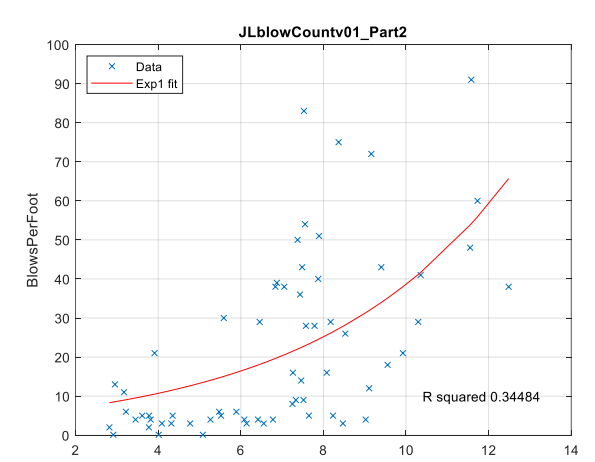
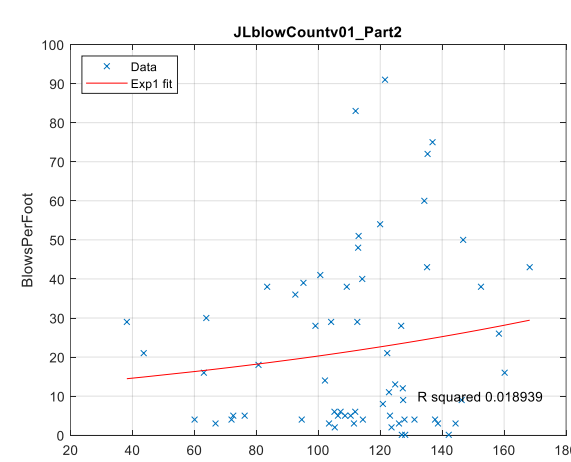
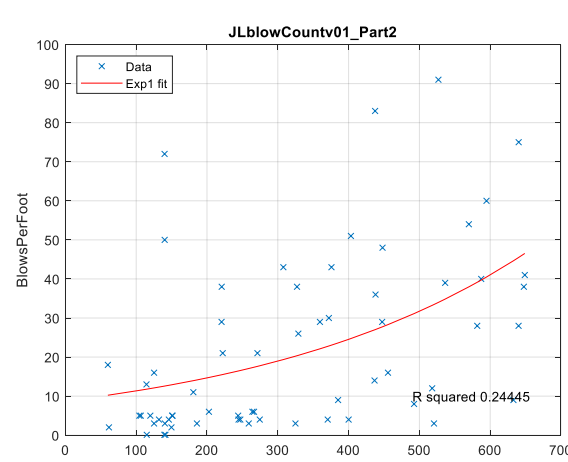
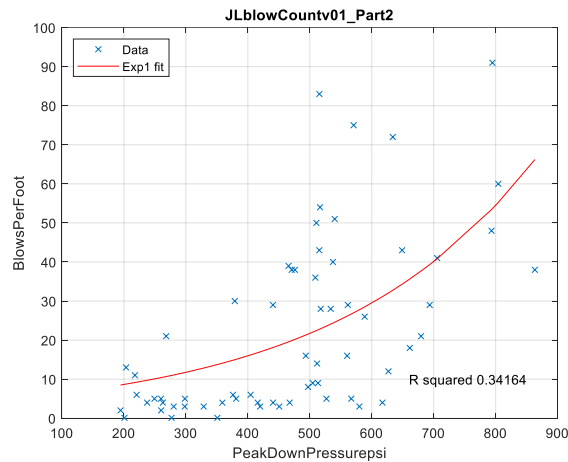
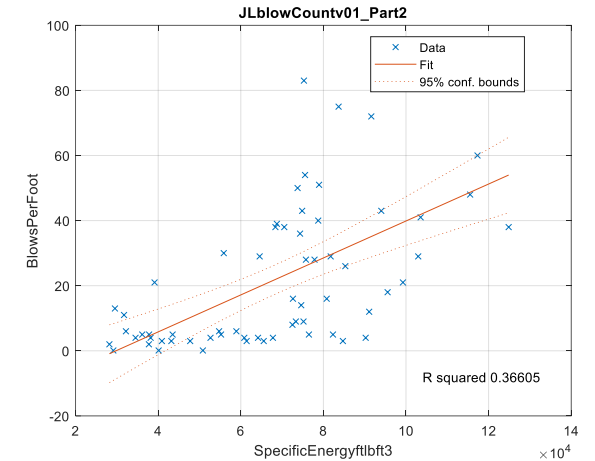
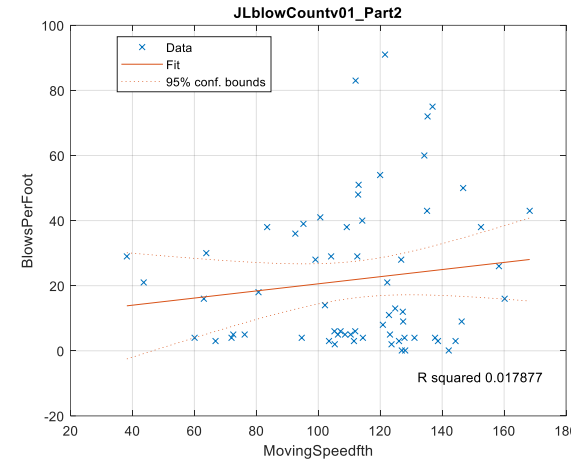
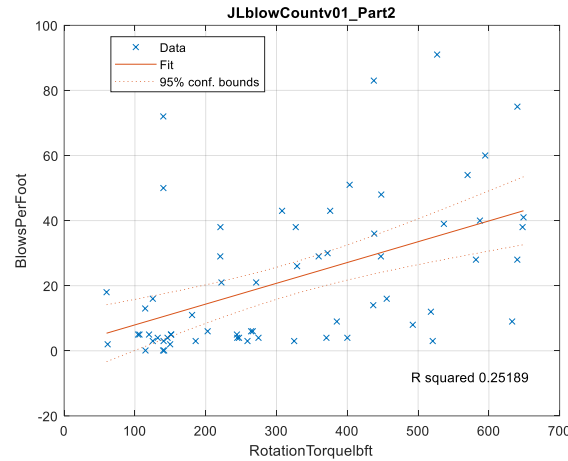
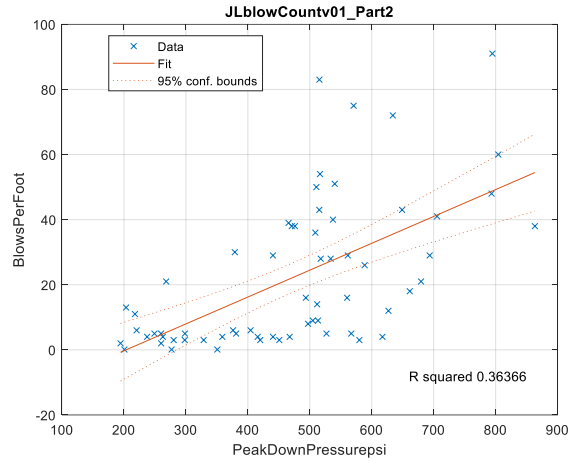


Analysis approaches

- Phase 1 – single parameter linear and exponential regression
 - Four MWD parameters, specific energy and depth (6 inputs) vs. Blow count, UCS, Unit Weight
- Phase 2 – multiple parameter linear regression (MLR)
 - All possible combinations (63) of 6 inputs (above) to predict Blow count, UCS, Unit Weight
- Phase 3 – multiple parameter nonlinear analysis (artificial neural networks - ANN)
 - All combinations (63) of 6 inputs (see previous) to predict Blow count, UCS, Unit Weight

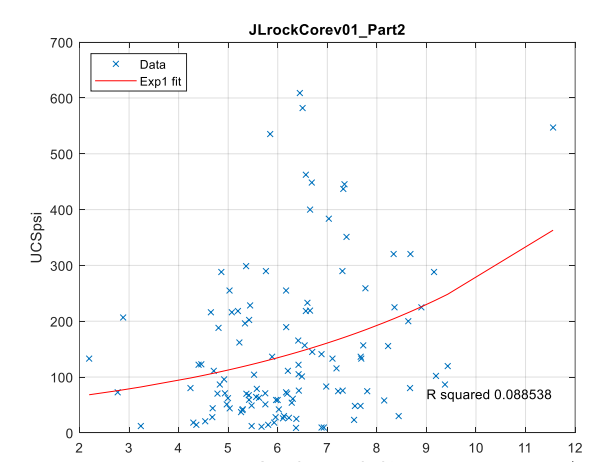
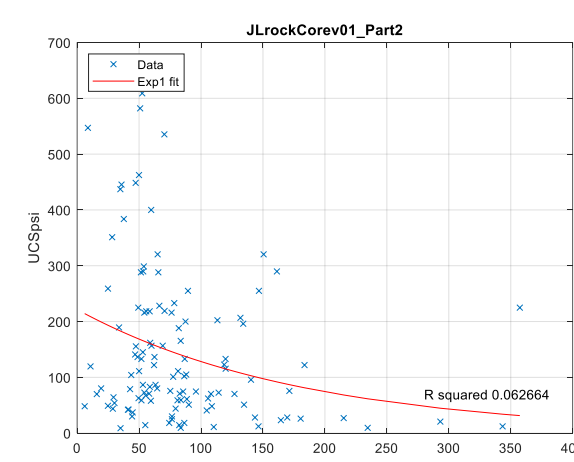
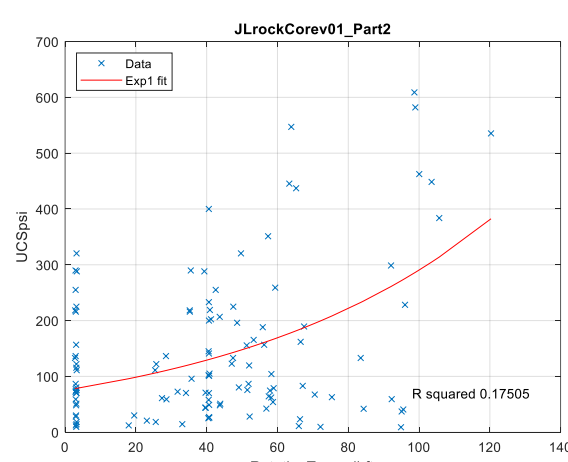
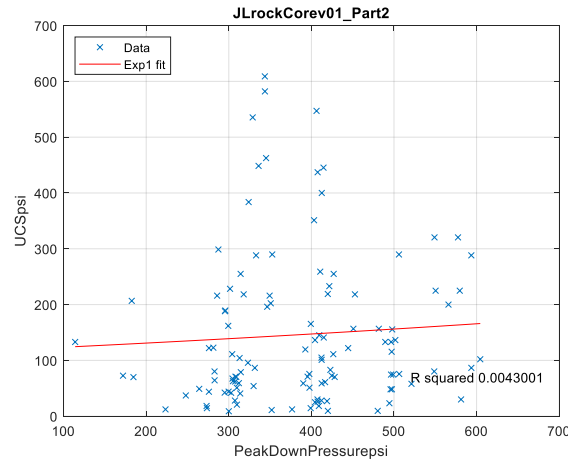
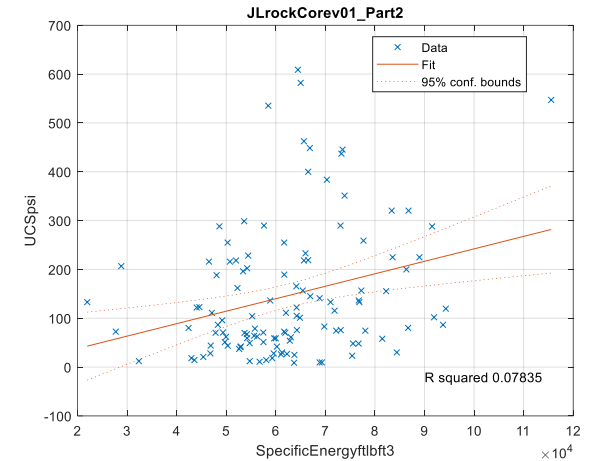
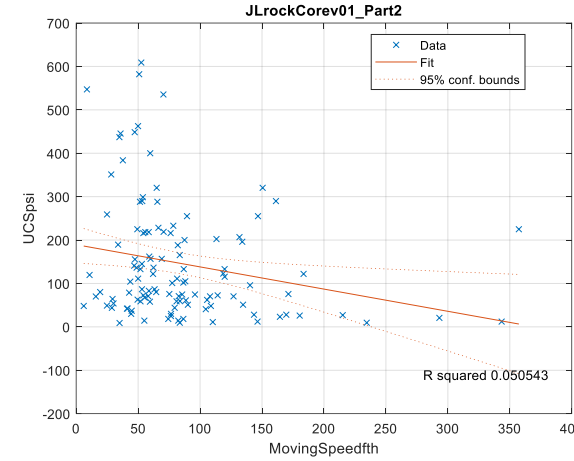
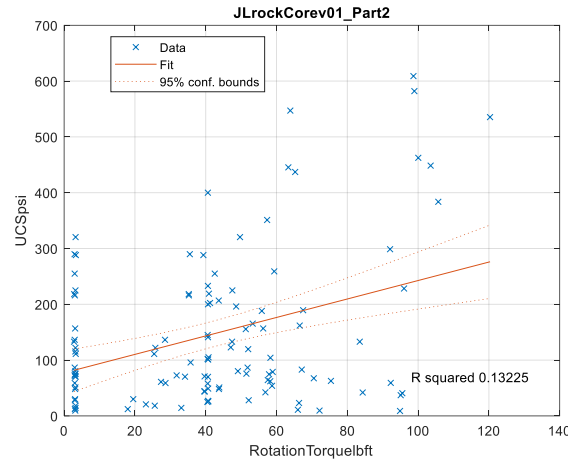
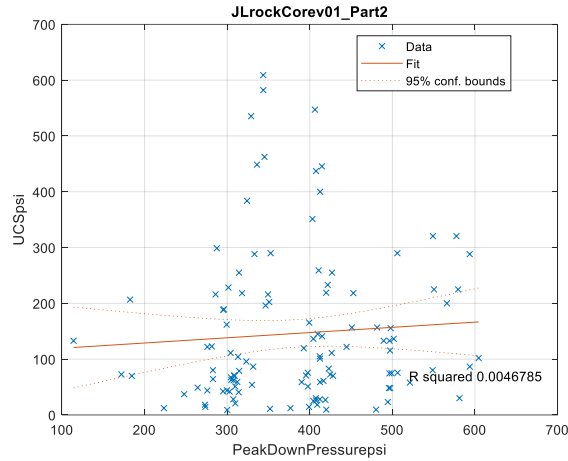
Phase 1 - Single parameter linear and exponential regression: **SPT N**

(Note: not showing depth or rotation speed correlations)



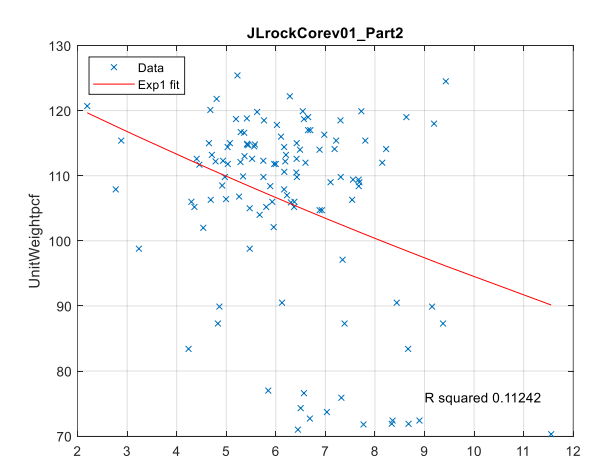
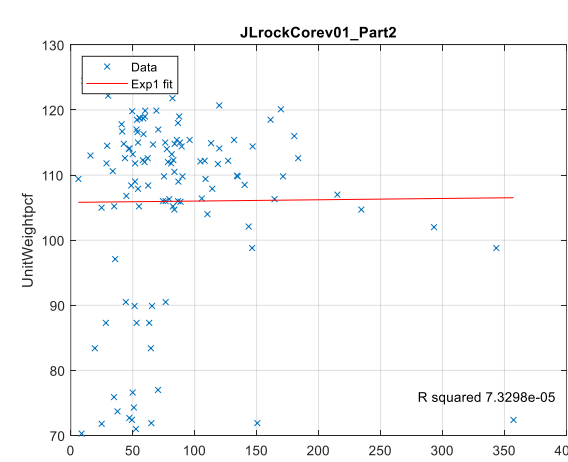
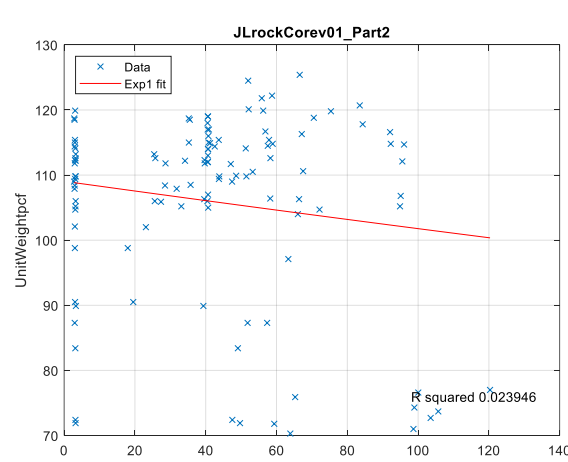
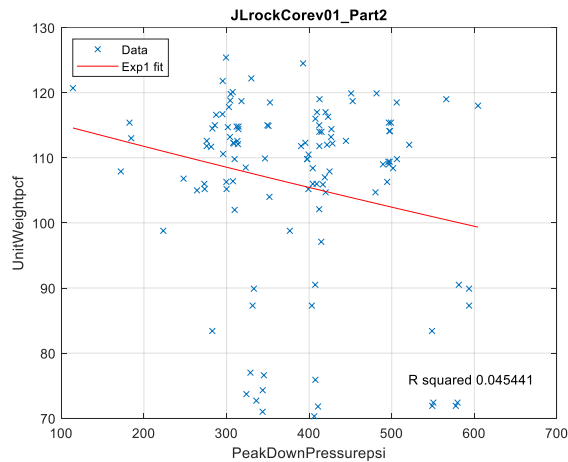
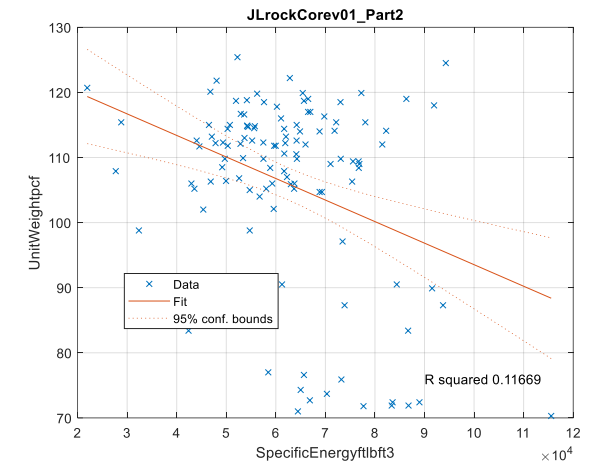
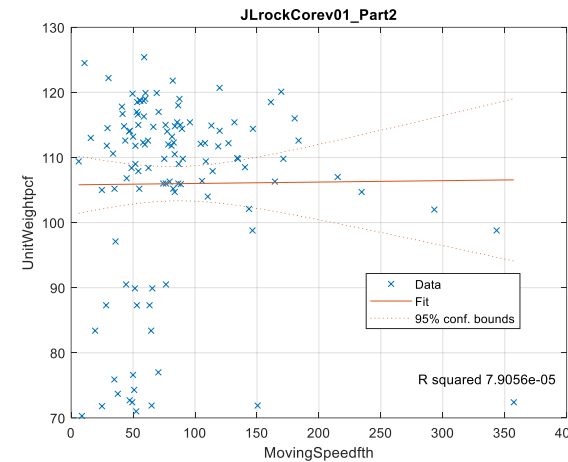
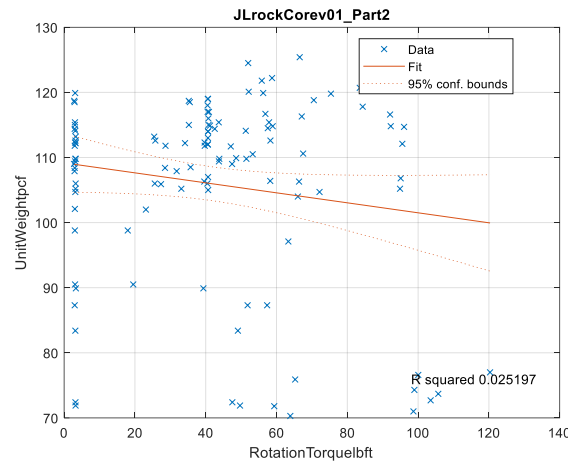
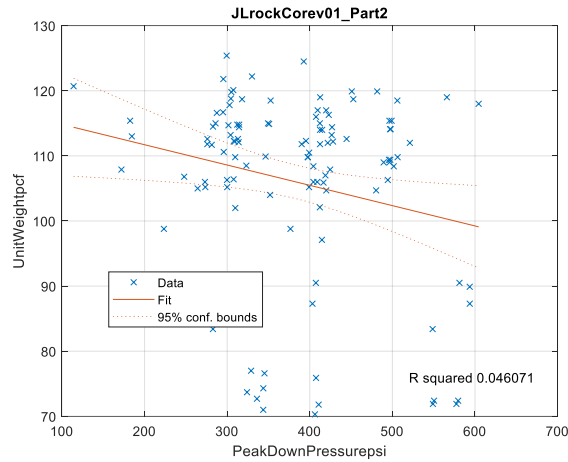
Phase 1 - Single parameter linear and exponential regression: UCS

(Note: not showing depth or rotation speed correlations)



Phase 1 - Single parameter linear and exponential regression: Unit Weight

(Note: not showing depth or rotation speed correlations)



Phase 1 - Single parameter linear and exponential regression - Summary

	SPT N (n = 64)		UCS (psi) (n = 117)		Unit weight (pcf) (n = 117)	
MWD input	<i>Linear R²</i>	<i>Exponential R²</i>	<i>Linear R²</i>	<i>Exponential R²</i>	<i>Linear R²</i>	<i>Exponential R²</i>
<i>Depth</i>	0.51	0.49	0.01	0.11	0.19	0.19
<i>Down pressure</i>	0.36	0.34	0.00	0.00	0.05	0.05
<i>Rotation torque</i>	0.25	0.24	0.13	0.17	0.03	0.02
<i>Rotation speed</i>	0.01	0.01	0.10	0.11	0.01	0.01
<i>Rate of advance</i>	0.02	0.02	0.05	0.06	0.00	0.00
<i>Specific energy</i>	0.37	0.34	0.08	0.09	0.12	0.11

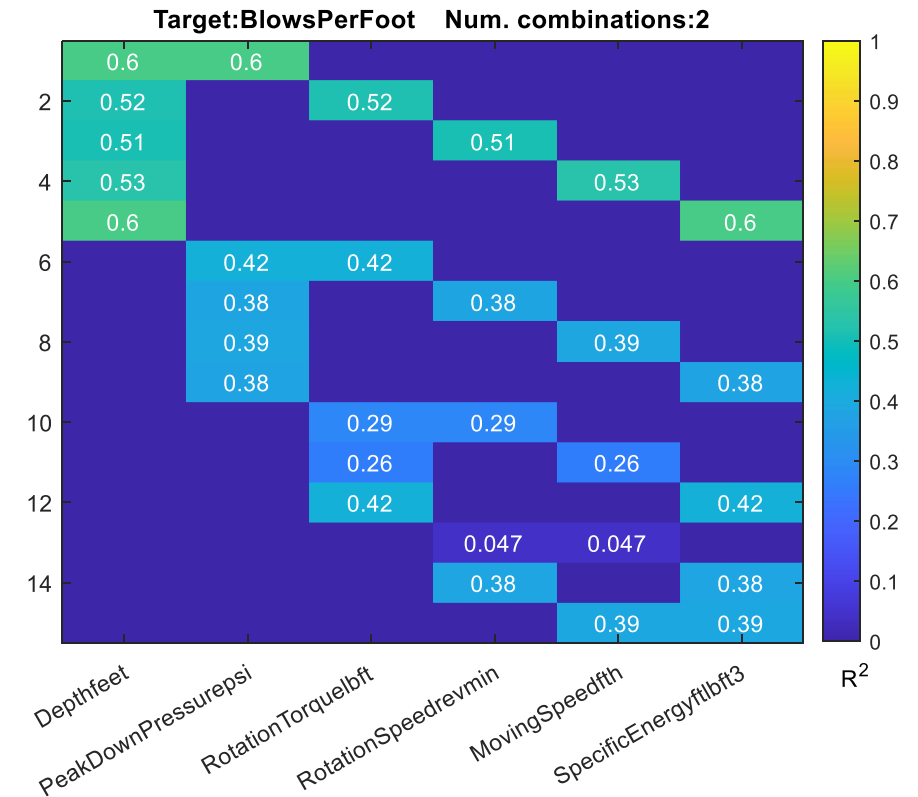
- Low correlation coefficients (see previous plots)
- Poor predictive capability

Phase 2 - multiple parameter linear regression (MLR)

63 combinations

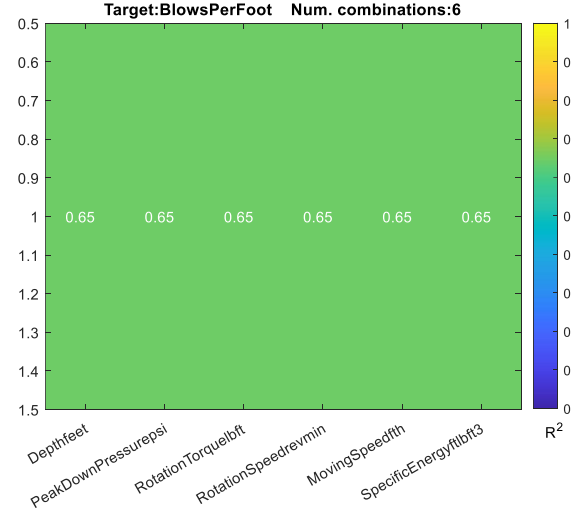
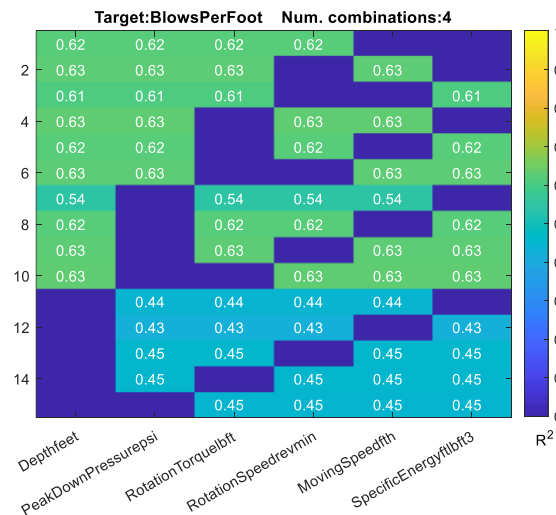
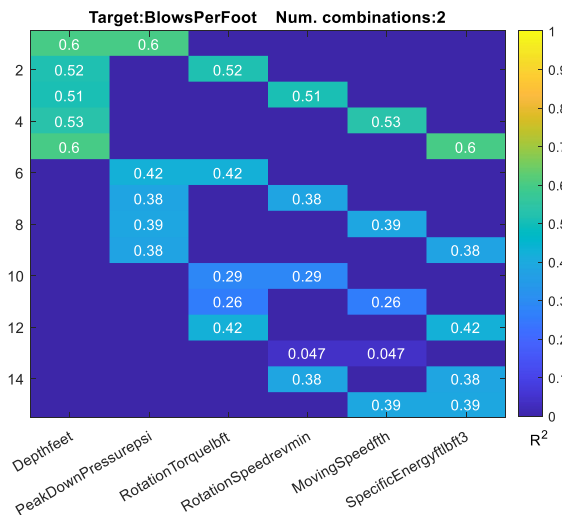
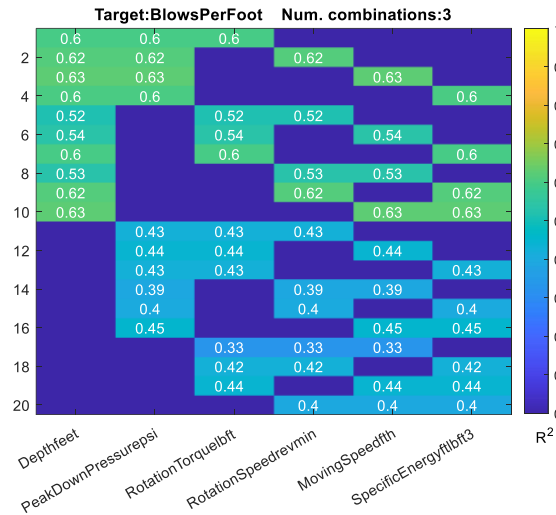
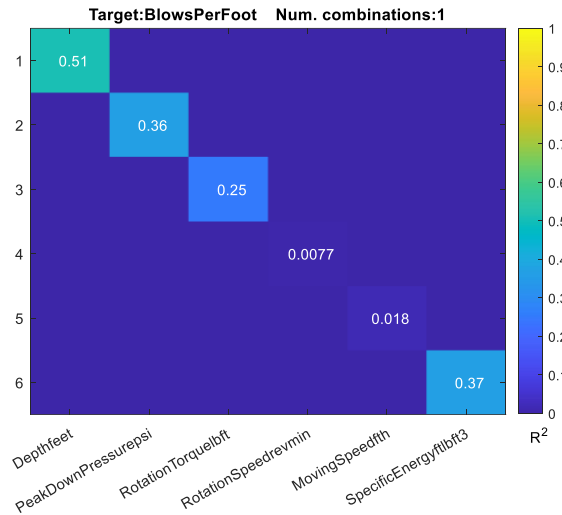
Following show MLR results in matrix form:

- Columns show six possible inputs
- Rows show combination of inputs
- Regression coefficient value shown in each cell in rows
- Color scale is 0 to 1 representing regression coefficient
- Color scale ranges from blue (0) to yellow (1)
- See example at right



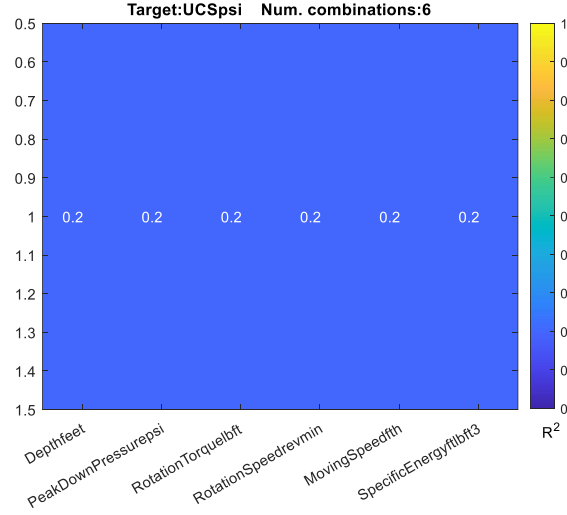
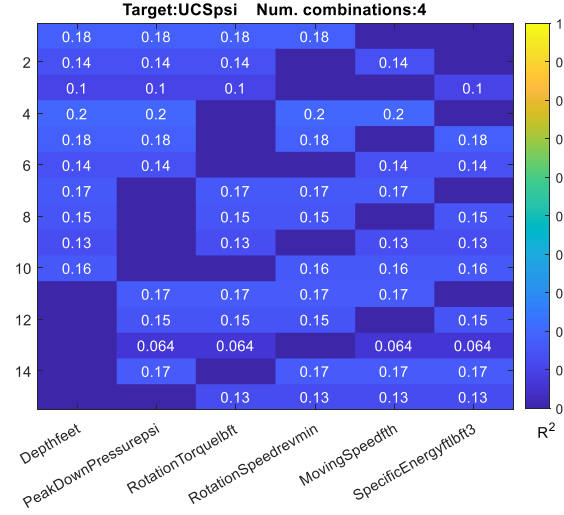
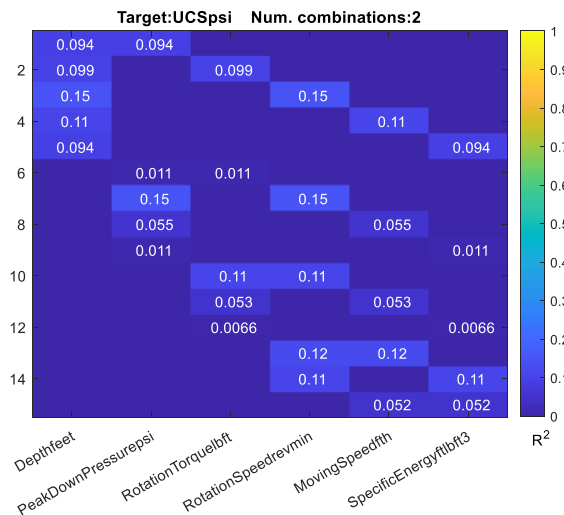
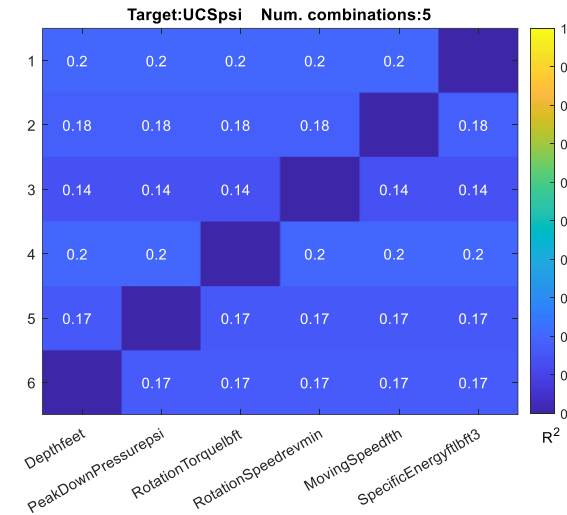
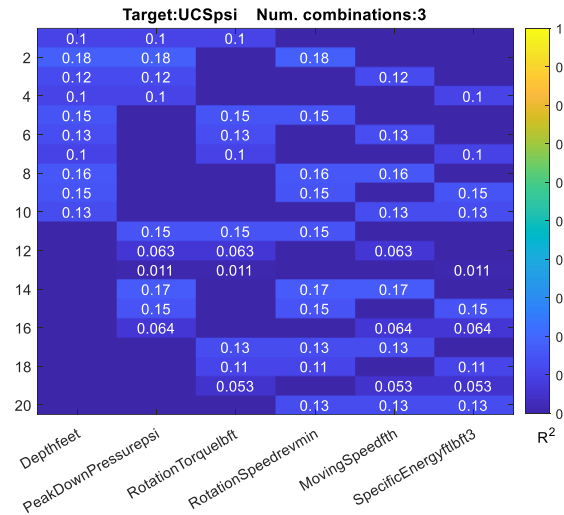
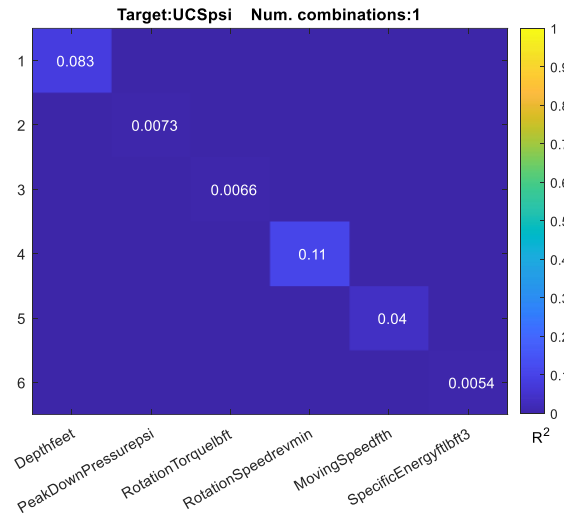
Note: inclusion of depth as a parameter

Phase 2 - multiple parameter linear regression – SPT N



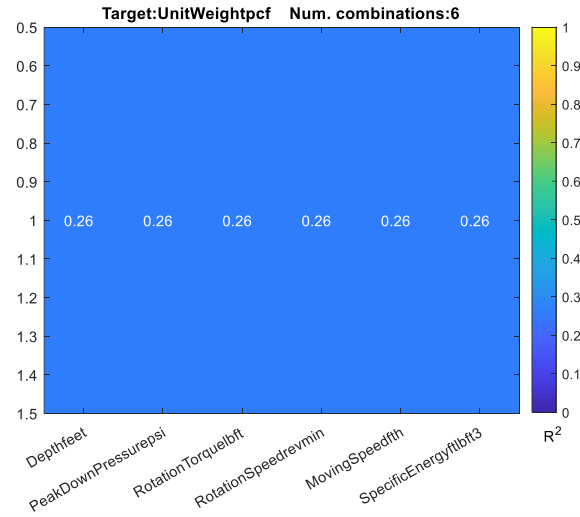
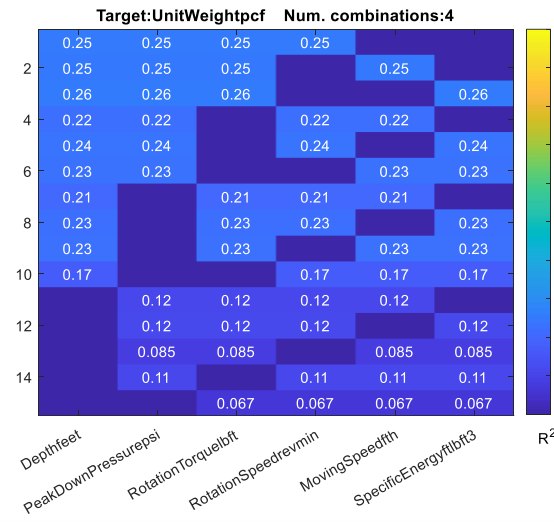
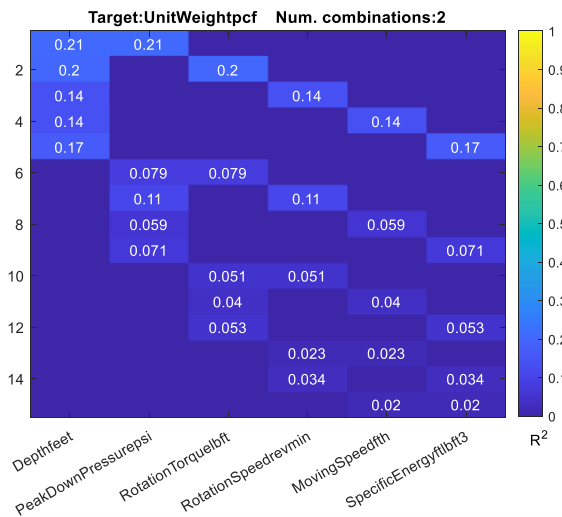
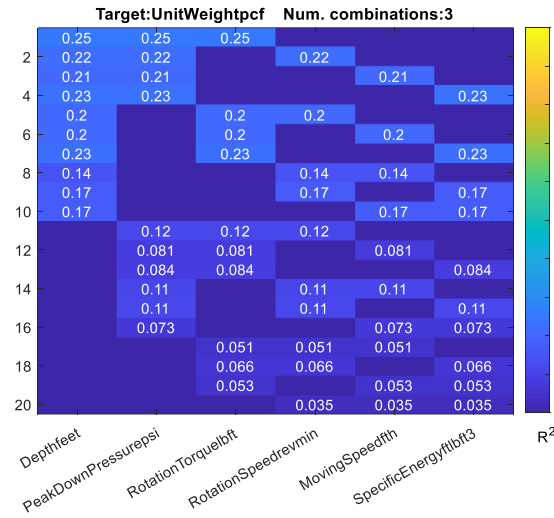
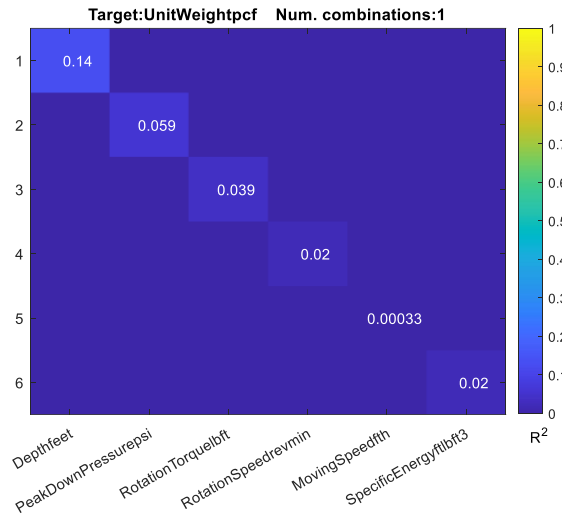
- SPT correlation coefficients significantly improved to approximately 0.6 range (light green)
- Improved predictive capability

Phase 2 - multiple parameter linear regression – UCS



- UCS correlation coefficients slightly improved to approximately 0.2 range (light blue)
- Little improvement in predictive capability

Phase 2 - multiple parameter linear regression – Unit weight



- Unit weight correlation coefficients slightly improved to approximately 0.25 range (light blue)
- Not much improvement in predictive capability

- Linear (and exponential) fitting:

- Poor results
- Low predictive power
- Lost cause?

Now
what?



Phase 3 – multiple parameter nonlinear analysis (fitting neural network - ANN)

6 possible inputs:

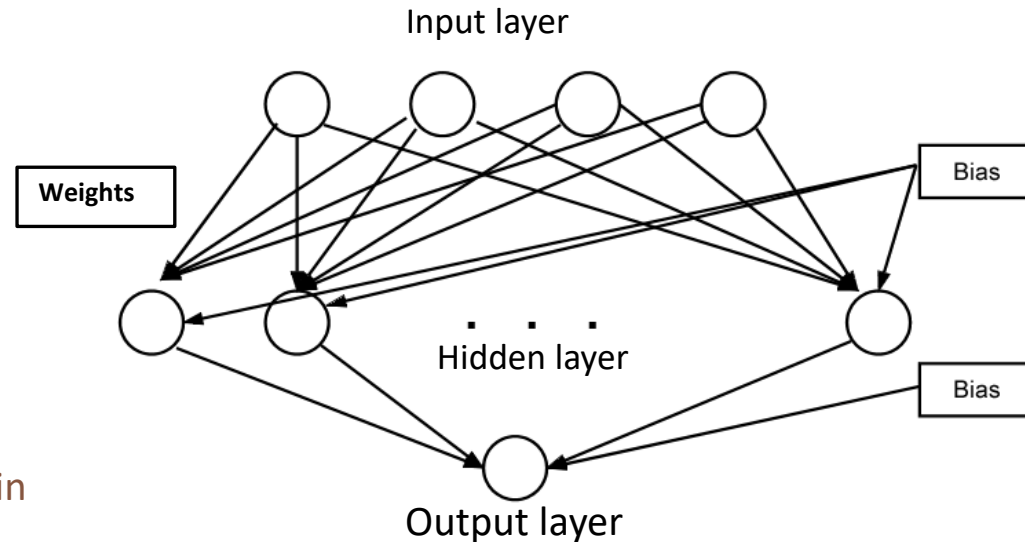
- Peak down pressure (psi)
- Rotation torque (lb-ft)
- Rotation speed (rev/min)
- Moving speed (ft/h)
- Depth (ft)
- Specific energy (ft bl/ft³)

1 hidden layer:

- Vary number of neurons in hidden layer:
2 3 5 7 9 10 11 15 20 25 30

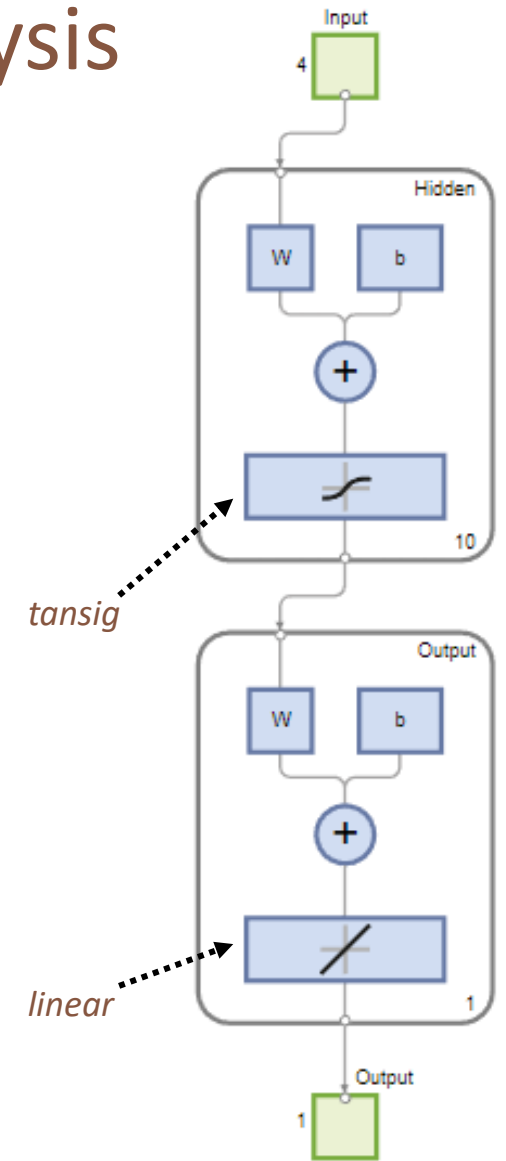
1 output layer:

- Single neuron



Stochastic/iterative process:

- Each NN model initializes with random weights and biases
- Each NN model uses a random partitioning of data inputs into training, validation and testing subsets

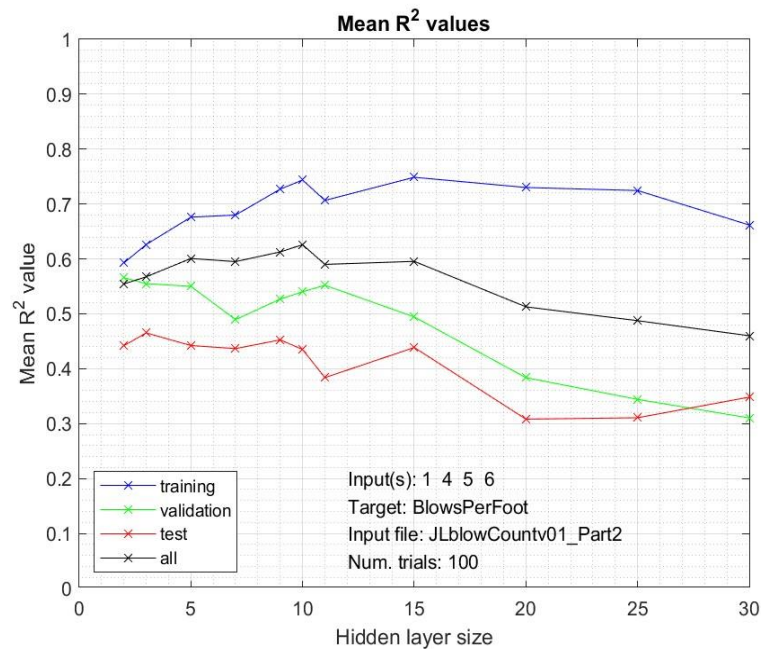


Useful reference: Neural Network Design,
Hagan, Demuth, Beale, De Jesus, 2nd Edition

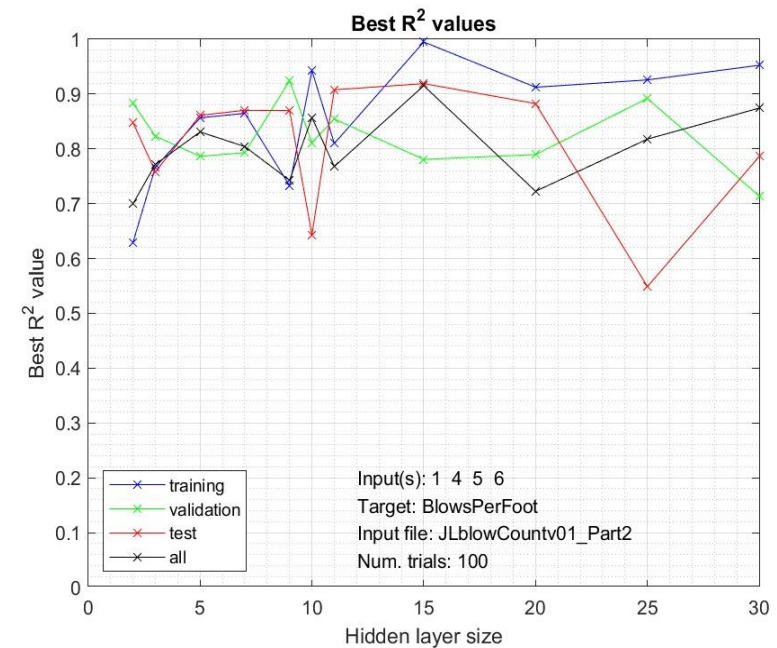
Neural network results – SPT N

- Training subset – 70%
 - Validation subset – 15%
 - Testing subset – 15%
 - All – 100%
- Possible training inputs:
 - 1 - Depth
 - 2 - PeakDownPressurepsi
 - 3 - RotationTorquelbft
 - 4 - RotationSpeedrevmin
 - 5 - MovingSpeedfth
 - 6 - Specific energy
 - Training target:
 - BlowsPerFoot
 - Number of blow count values = 64

Mean R^2 regression results over 100 trials



Best R^2 regression results over 100 trials

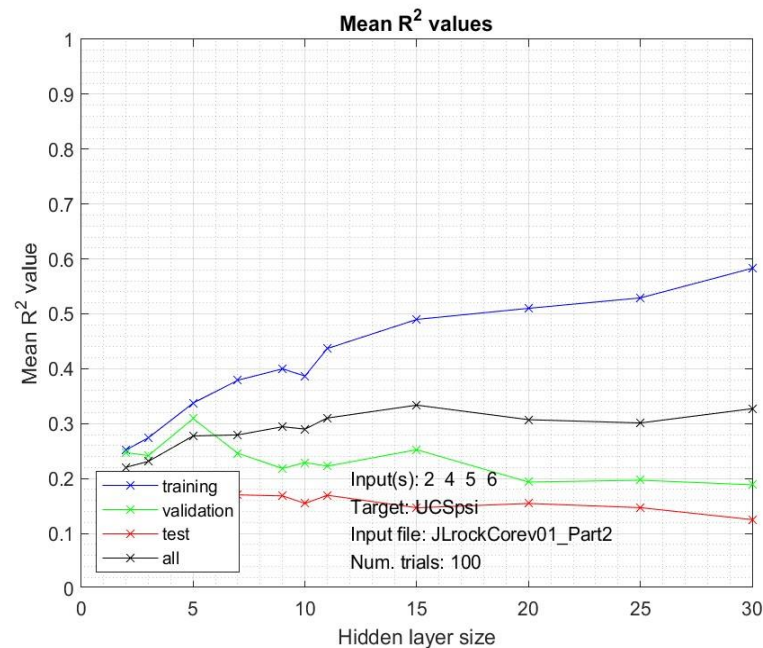


Neural network results – UCS

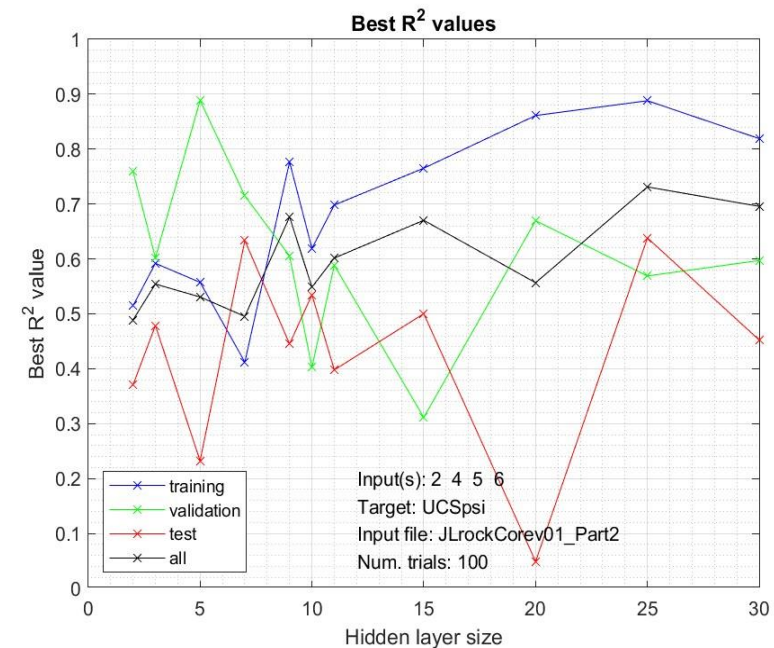
- Training subset – 70%
 - Validation subset – 15%
 - Testing subset – 15%
 - All – 100%
- Possible training inputs:
 - 1 - Depth
 - 2 - PeakDownPressurepsi
 - 3 - RotationTorquelbft
 - 4 - RotationSpeedrevmin
 - 5 - MovingSpeedfth
 - 6 - Specific energy

- Training target:
 - UCSpsi
 - Number of blow count values = 117

Mean R^2 regression results over 100 trials



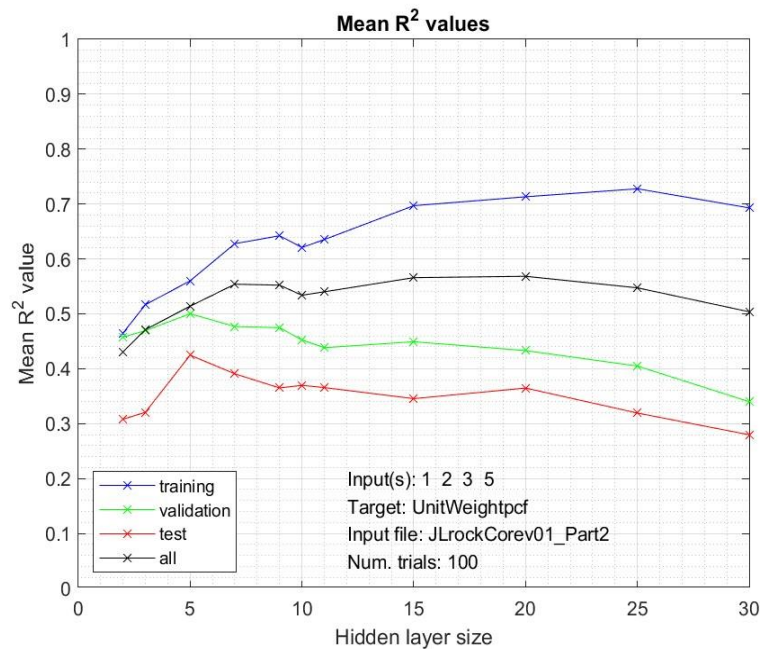
Best R^2 regression results over 100 trials



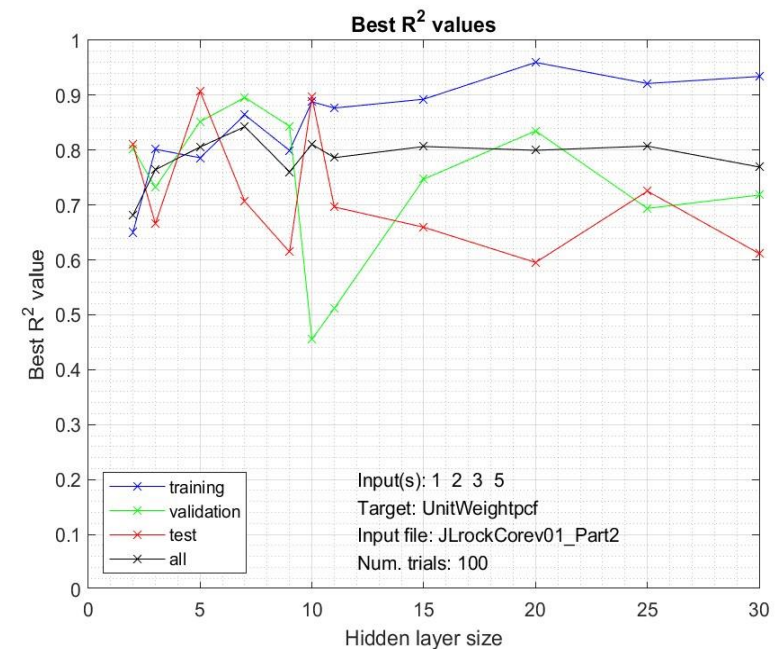
Neural network results – Unit Weight

- Training subset – 70%
 - Validation subset – 15%
 - Testing subset – 15%
 - All – 100%
- Possible training inputs:
 - 1 - Depth
 - 2 - PeakDownPressurepsi
 - 3 - RotationTorquelbft
 - 4 - RotationSpeedrevmin
 - 5 - MovingSpeedfth
 - 6 - Specific energy
 - Training target:
 - Unitweightpcf
 - Number of blow count values = 117

Mean R^2 regression results over 100 trials



Best R^2 regression results over 100 trials



Best NN results – SPT N

List of models with high R^2 values for SPT NN modelling

Depth	Down pressure	Rotation torque	Rotation speed	Moving speed	Specific energy	HL no.	Sum R^2	Avg. R^2
✓	✓		✓	✓		9	3.54	0.89
✓			✓	✓	✓	15	3.61	0.90
✓	✓	✓	✓	✓		10	3.51	0.88
✓	✓	✓	✓	✓		15	3.64	0.91
✓	✓	✓	✓		✓	9	3.53	0.88
✓	✓		✓	✓	✓	11	3.52	0.88

Best NN results – UCS

List of models with high R^2 values for UCS NN modelling

Depth	Down pressure	Rotation torque	Rotation speed	Moving speed	Specific energy	HL no.	Sum R^2	Avg. R^2
✓				✓		10	2.77	0.69
			✓		✓	20	2.86	0.72
	✓	✓		✓	✓	30	2.99	0.75
	✓		✓	✓	✓	25	2.83	0.71

Best NN results – Unit Weight

List of models with high R^2 values for Unit Weight NN modelling

Depth	Down pressure	Rotation torque	Rotation speed	Moving speed	Specific energy	HL no.	Sum R^2	Avg. R^2
✓	✓	✓				25	3.43	0.86
✓		✓			✓	25	3.32	0.83
✓	✓	✓		✓		5	3.35	0.84
✓	✓	✓		✓		7	3.31	0.83
✓		✓	✓		✓	20	3.35	0.84
	✓	✓	✓		✓	9	3.35	0.84
✓	✓	✓	✓		✓	9	3.32	0.83

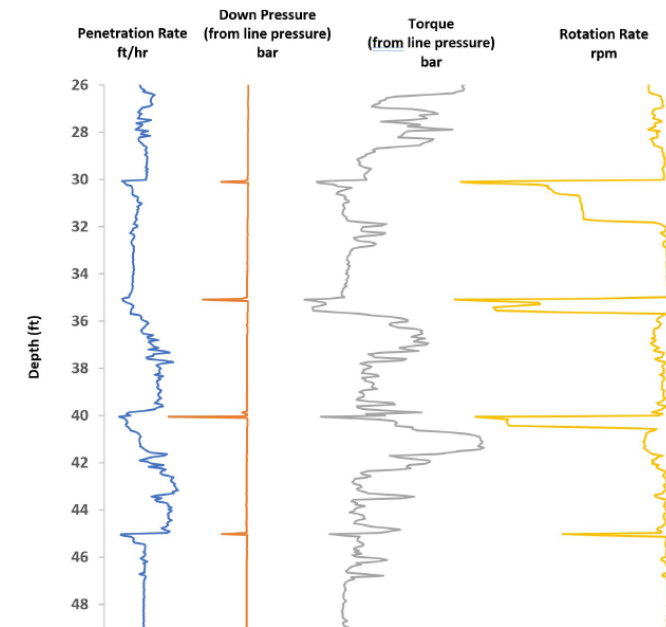
Conclusions and takeaways

- Problem appears to be nonlinear; at least for Montana IGMs
- Single and multiple parameter linear correlations give poor results
- Using a compound parameter (a function of 4 individual MWD parameters i.e. specific energy), gives somewhat better linear correlations
- Depth is an important predictive parameter
- A nonlinear approach (ANN) using combinations of individual parameters as inputs gives much improved prediction capability
- Ranked best predictive results:
 1. SPT blow counts
 2. Unit weight
 3. UCS



“MWD will improve the way we characterize materials, especially within harder materials like partially weathered rock where SPTs meet refusal and CPTs provide limited or no information, and high-quality rock cores may be difficult to obtain.”

Rivers & Rogers, Geostrata

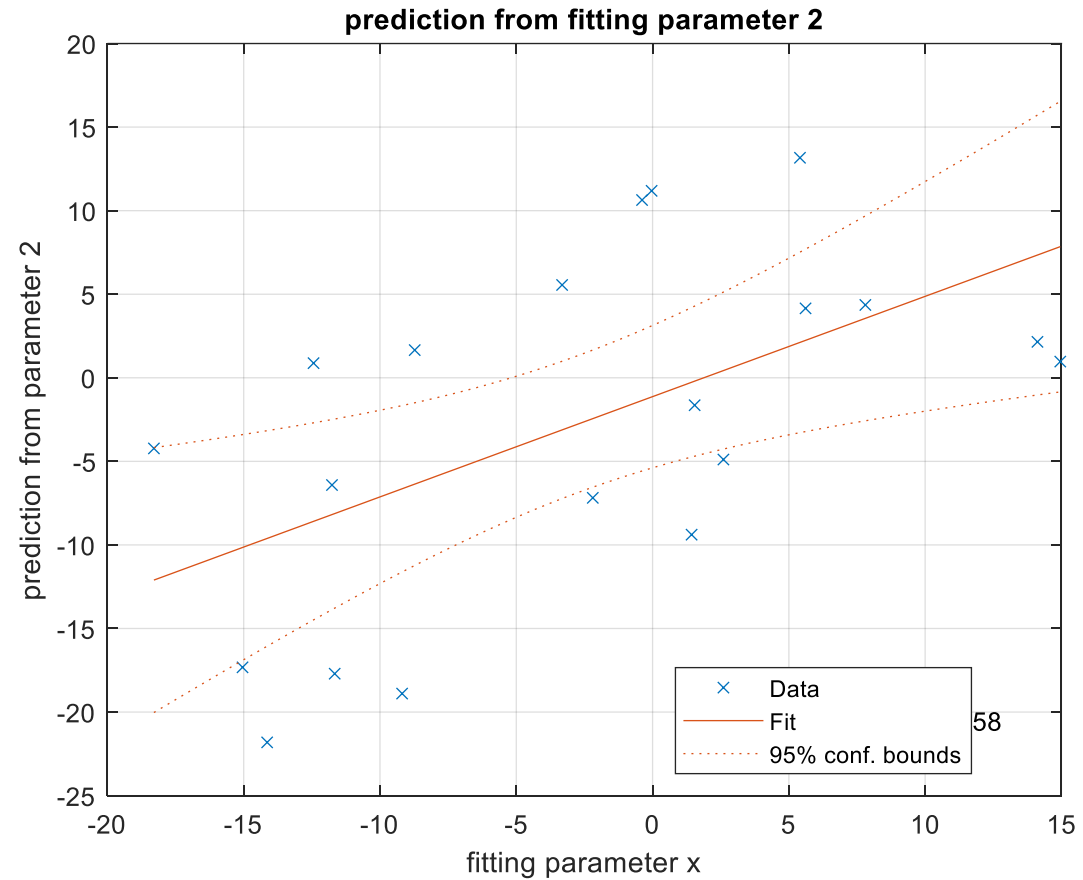


Geostrata, Dec 23/Jan 24, Lindenbach et al.

Example of fitting multiple parameter data

Prediction of measured data using parameter x.

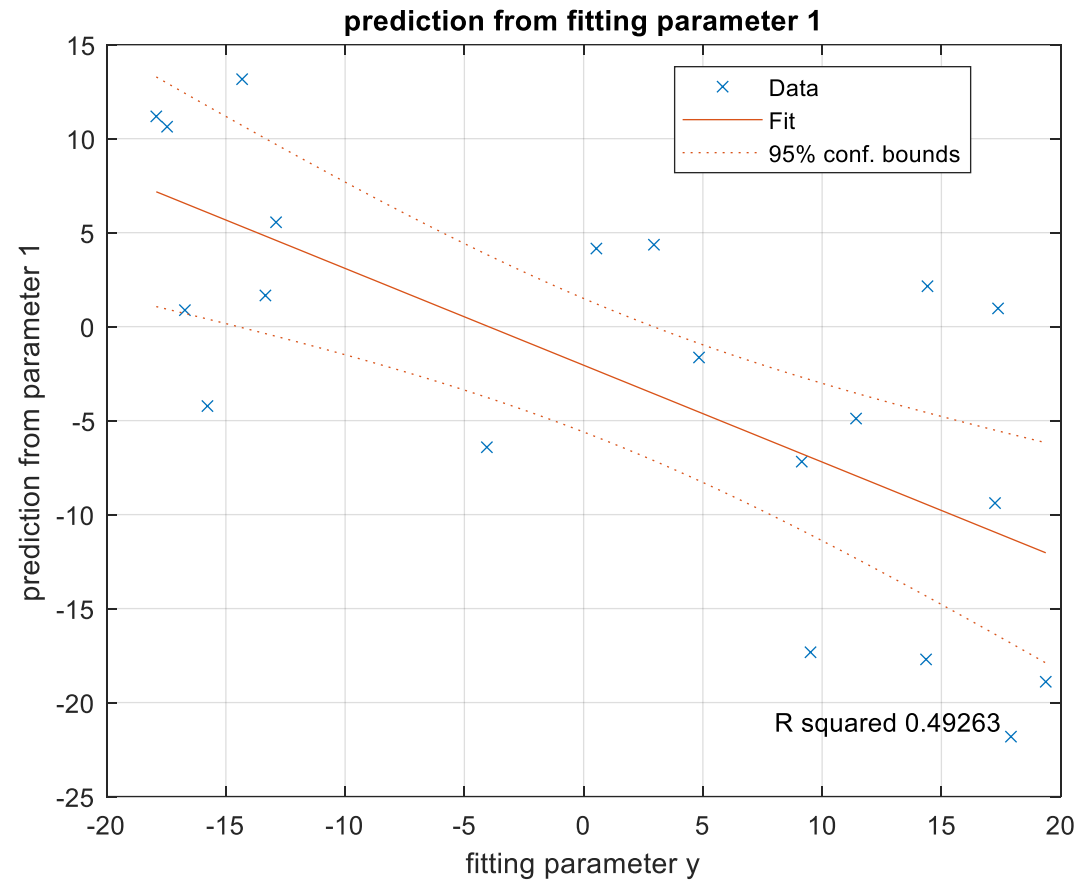
Analogous to predicting e.g. SPT blow count using MWD parameter 1.



Example of fitting multiple parameter data cont.

Prediction of measured data using parameter y .

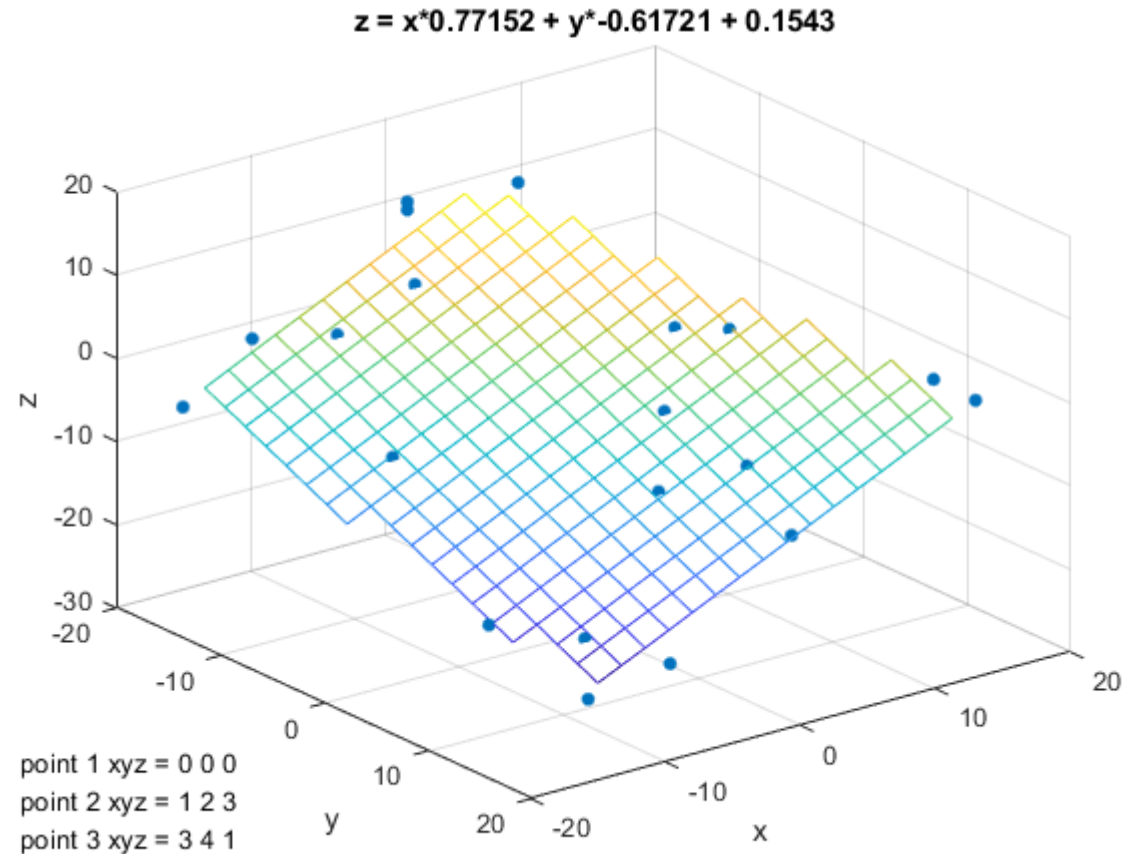
Analogous to predicting e.g. SPT blow count using MWD parameter 2.



Example of fitting multiple parameter data cont.

Prediction of measured data using
multiple parameters x and y.

Analogous to predicting e.g. SPT blow
count using two MWD parameters.



Example of fitting multiple parameter data concl.

Prediction of measured data
using multiple parameters x
and y.

Analogous to predicting e.g.
SPT blow count using two
MWD parameters.

----- Linear regression parameter 1 -----

rSq =
0.49263

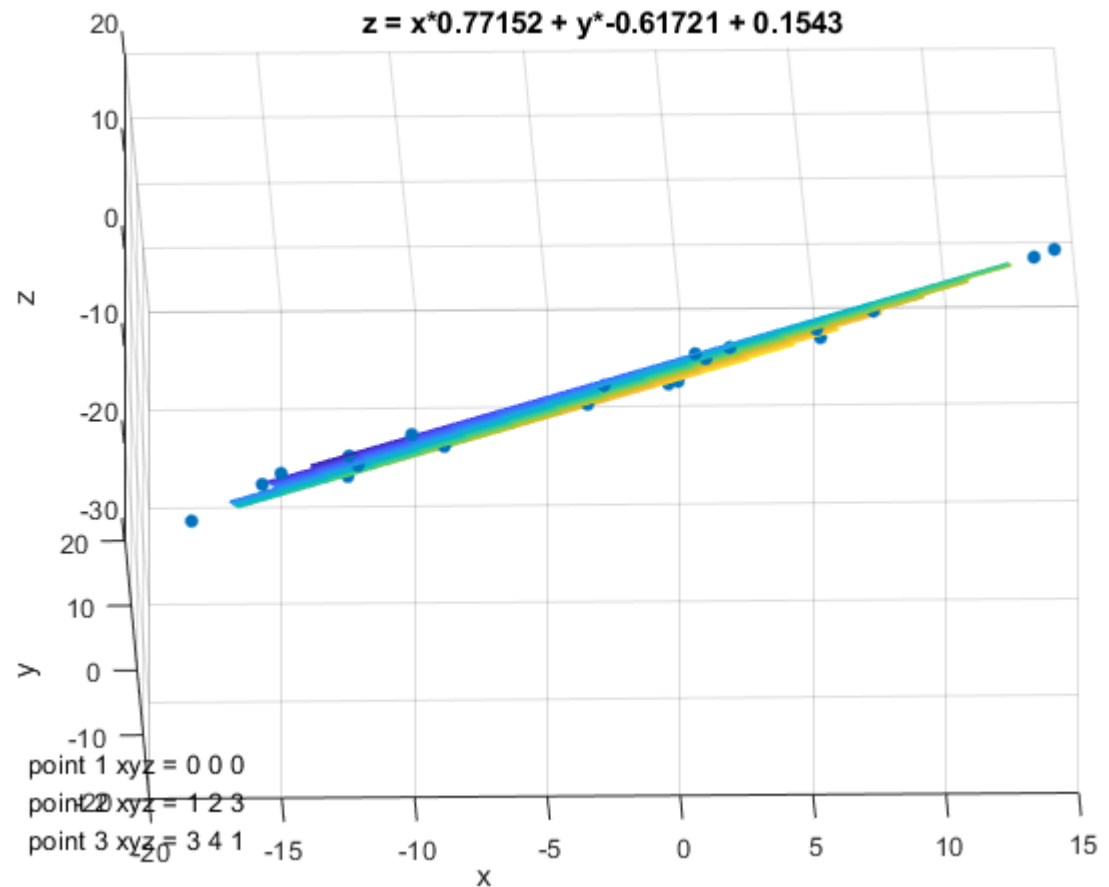
----- Linear regression parameter 2 -----

rSq =
0.31858

----- Multiple Linear Regression -----

using fitting parameter 1 (y) and fitting
parameter 2 (x)

x and y predicting z - R squared = 0.99979



Rotation of previous plot showing almost perfect fit.

MWD Implementation Recommendations

Recommendation 1

Have the engineer/geologist actively involved with the MWD process from beginning to end

- Ideally, have the engineer/geologist do the actual drilling
- Understand the MWD instrumentation
- Reduction of variables
 - Continuous drilling versus sampling drilling
 - Standardization of drilling styles/preferences
 - Rotation speed
 - Down pressure
 - Moving speed
 - Different geologies impact these drilling styles

MWD Implementation Recommendations

Recommendation 2

Update models as MDT collects additional MWD data

- May have to create different models based on:
 - Geological setting
 - Drill rig type
 - Drilling depth
 - Shallow vs. deep
 - Similar to correction for blow counts
 - Drilling operator
 - Drilling method
 - Currently have hollow-stem auger and HQ rock coring in clay overlying IGMs of Eastern Montana

MWD Implementation Recommendations

Recommendation 3

- Correlations to direct measurement data
- Driven pile capacities
 - Pile driving analysis (PDA) data
 - Can MWD data accurately predict:
 - Soil resistance at different depths
 - Pile capacities
- Osterberg Cell
 - Can MWD predict ultimate skin friction and end-bearing capacities obtained from Osterberg Cell tests – drilled shaft