# Combining Physics-Based and Data-Driven Modeling for Pressure Prediction in Well Construction

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## Summary

This study presents a framework for combining physics-based and data-driven models to improve well construction.

The proposed approach aims to provide a more robust and accurate model that mitigates the disadvantages of using purely physics-based or data-driven models. Disadvantages may be:

Physics-based models:
- can be inaccurate if the physical dynamics are not fully accounted for.
- require a large amount of operator input and is liable to human error if it is not maintained and calibrated

Data-driven models:
- are black-box models which lack a connection to underlying physics and thereby complicating interpretability.
- often struggle to properly capture causal relationships.

A rule-based stochastic decision-making algorithm was developed to combine these models. The proposed approach shows potential to attain the best features of both approaches, and thereby allow for safer and more optimized well construction operations.

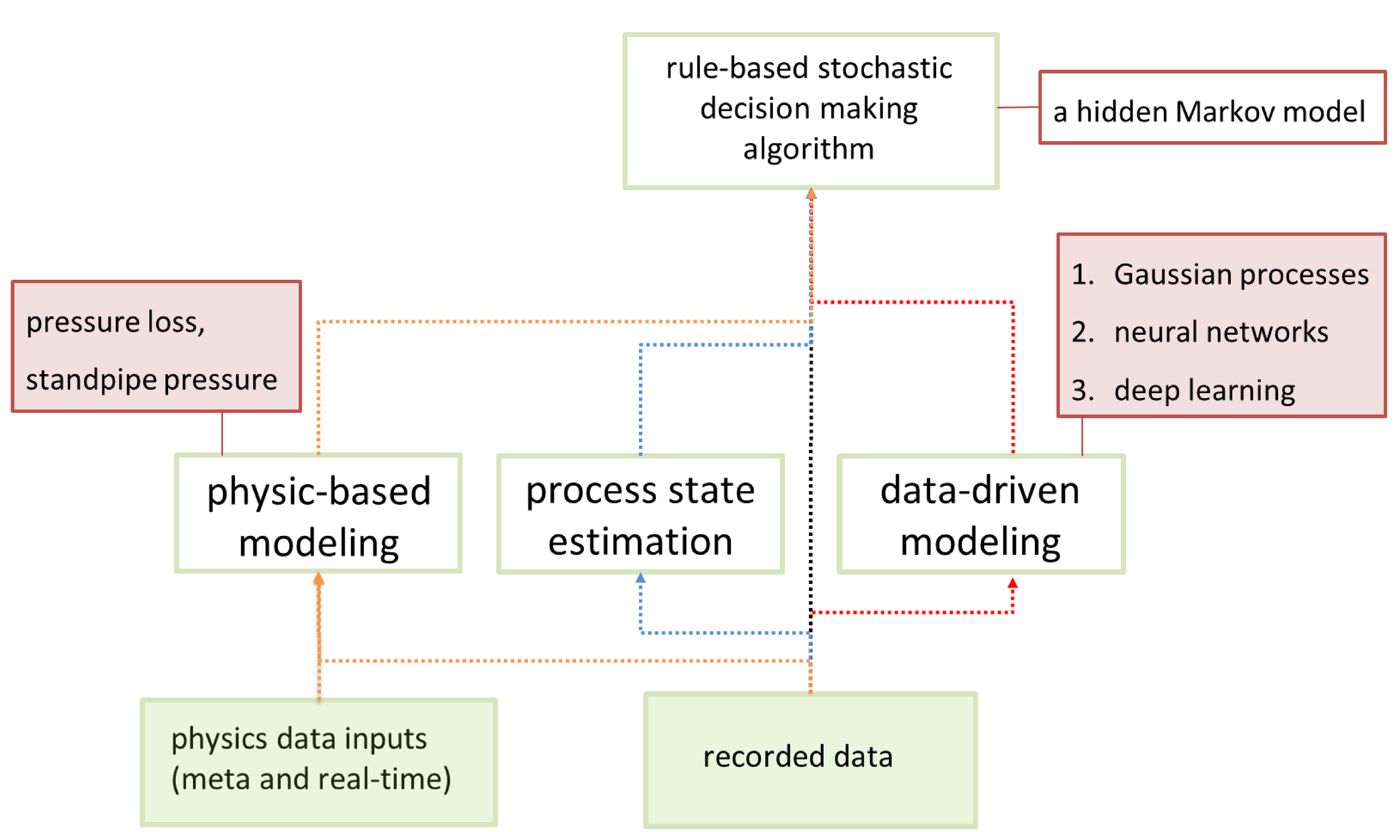
## Methods

Physics-based fluid flow models from the first principles are used in simulations to estimate the standpipe pressure (SPP).

Gaussian processes, neural networks and a deep learning model are trained using an actual well construction dataset.

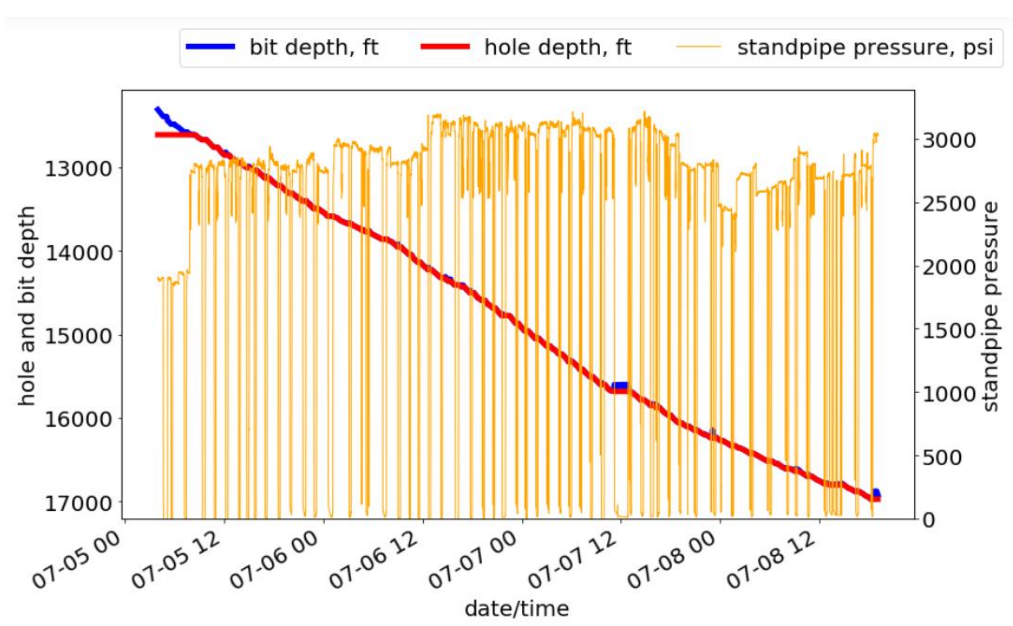
A hidden Markov model is developed that combines these results comprising of the process state and domain knowledge.

All results from the physics-based, data-driven and combination modeling are presented.

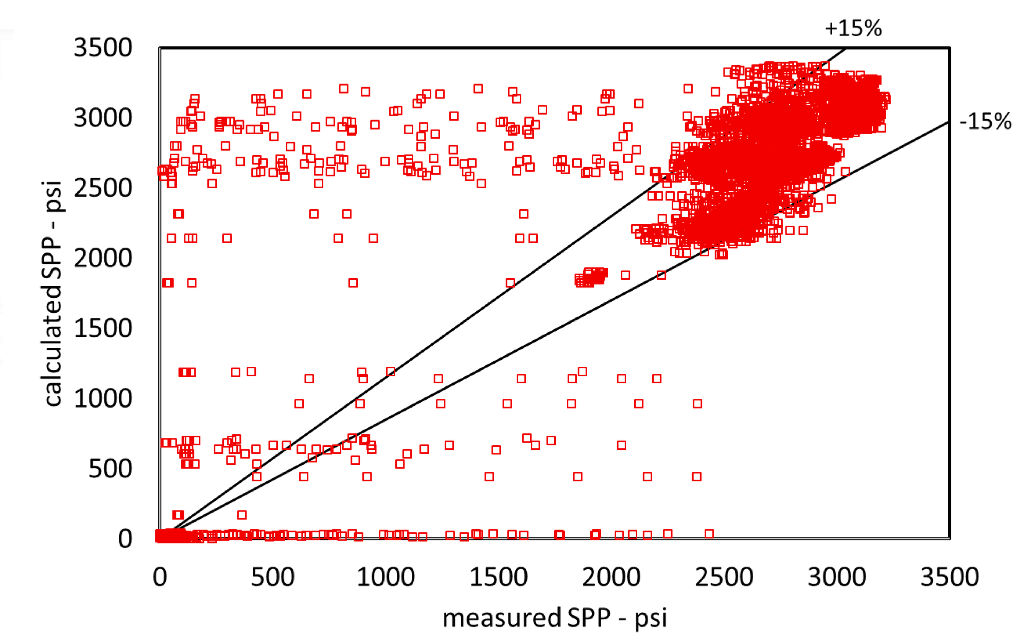



Combination of physics-based and data-driven modeling flow chart.

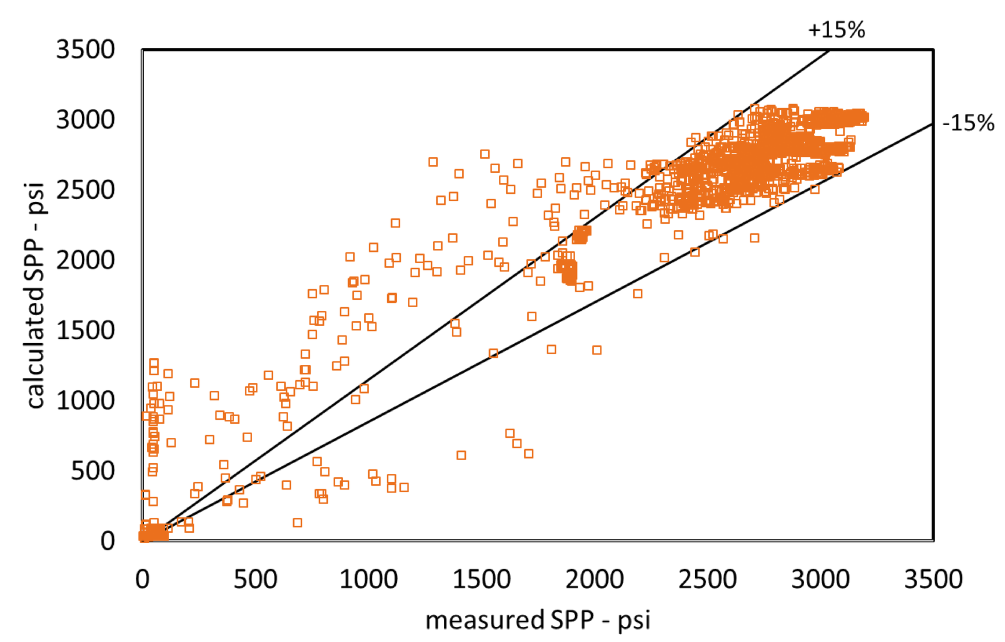
## Figures and Results



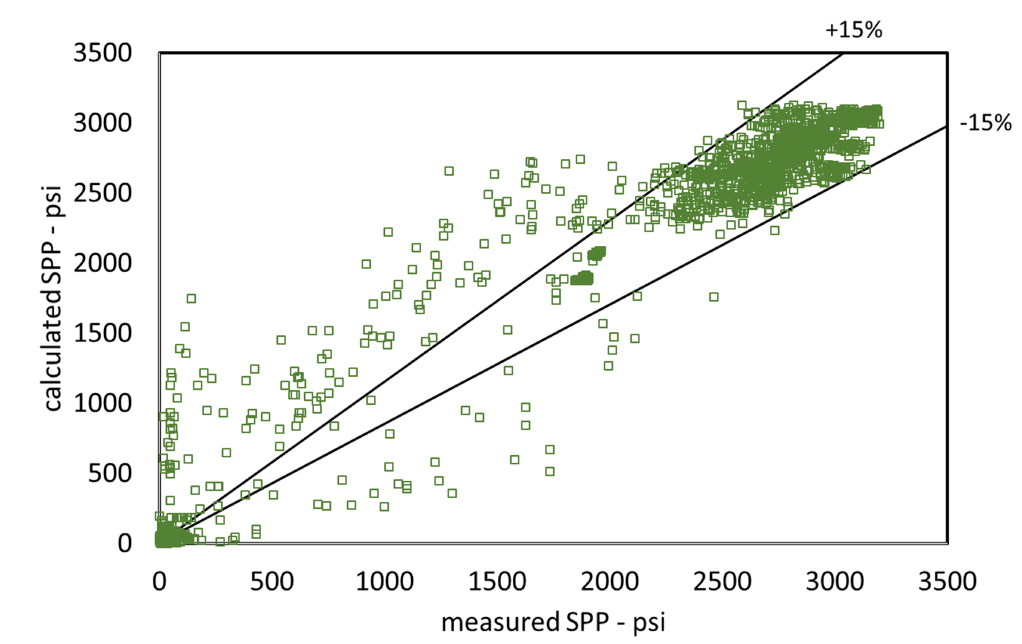

Well construction dataset from Well A.



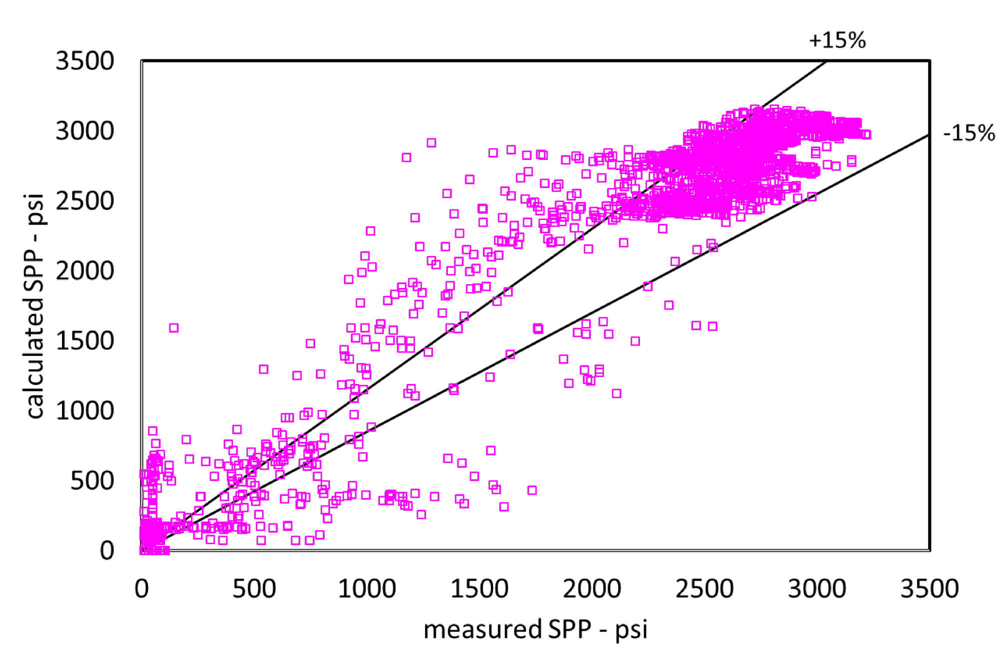

Physics-based model results of calculated vs. measured SPP values.



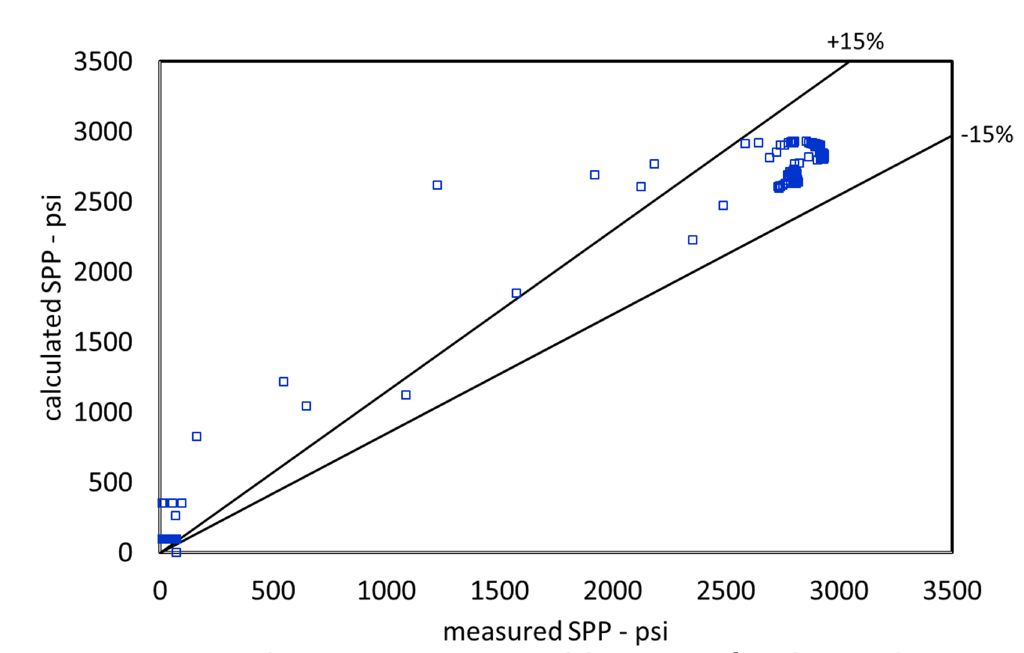

Neural networks, a single hidden layer, random sampling, and a 4-to-1 training-to-test ratio.




Neural networks, ten hidden layers, randomly sampling, and a 4-to-1 training-to-test ratio.




Neural networks, ten hidden layers, trained in sequential intervals.

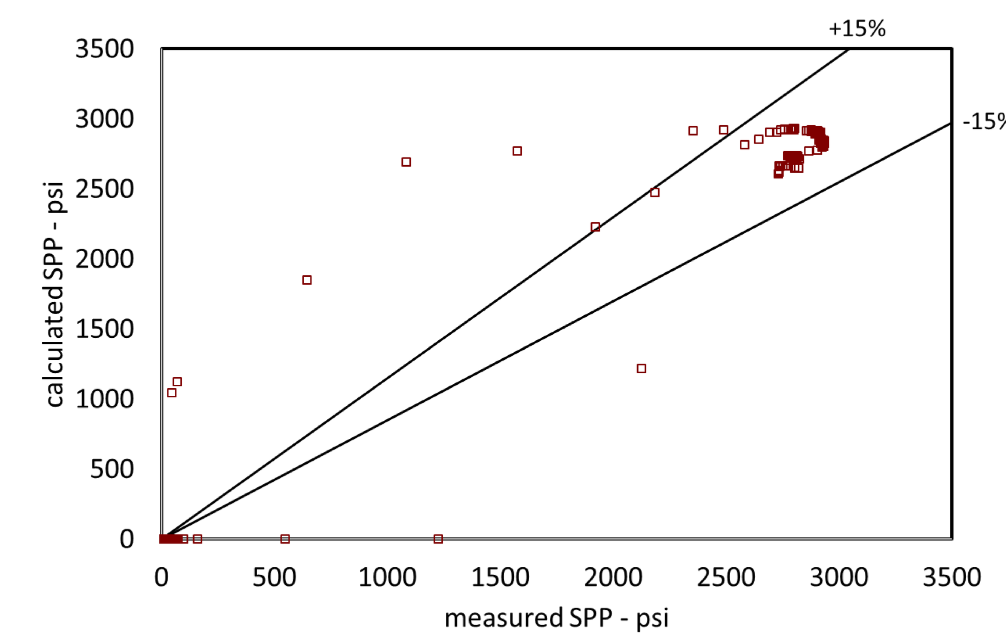



Gaussian Processes with a Matérn kernel.

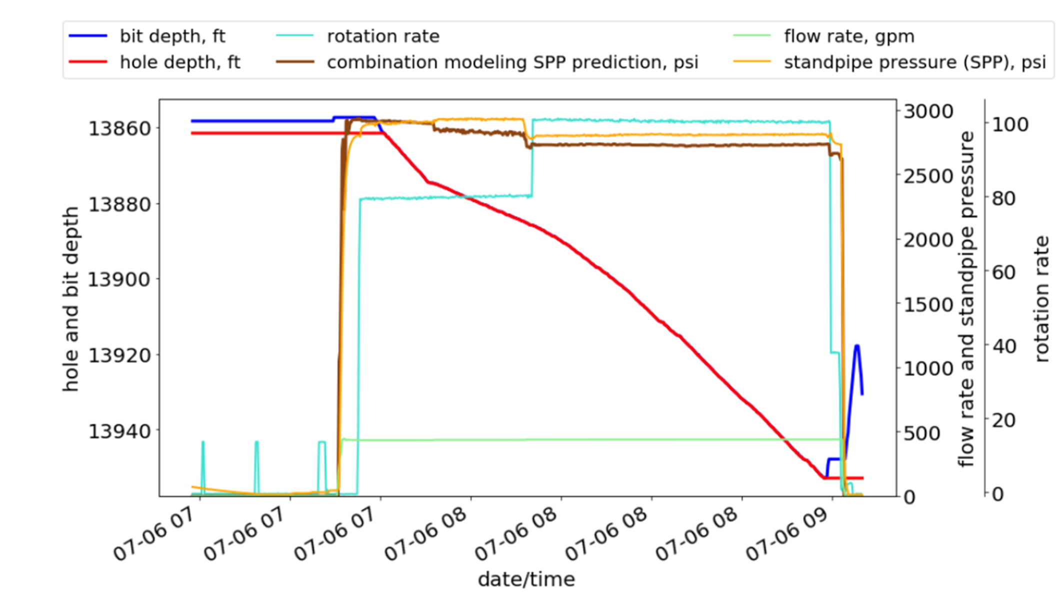
Several analyses were conducted to estimate the fluid circulating pressure in the wellbore, which is vital for safe and efficient well construction operations.

Note that the proposed framework is not limited to the prediction of circulating pressure and can be extended to other well construction domains.

## Conclusion




Combined modeling results. Physics-based model and GPs results are combined through the hidden Markov model.




Combined modeling results presented in time-series.

The combination modeling was able to provide better results and outperformed all others.

Through the proposed combination modeling, circulating pressure can be better predicted, which will lead to safer and more (cost-)efficient operations.

| | Root Mean Square Error (RMSE) | $R^2$ (Correlation) | Median Absolute Error | Mean Absolute Error |
|---|---|---|---|---|
| **Physics Modeling** | 619.49 | 0.6988 | 93.68 | 256.57 |
| **NN** [Single hidden layer, randomly sampled, 4 to 1 training/test ratio] | 163.52 | 0.9791 | 78.37 | 106.74 |
| **Deep Learning** [10 hidden layers, randomly sampled, 4 to 1 training/test ratio] | 158.05 | 0.9802 | 60.48 | 92.08 |
| **Deep Learning** [10 hidden layers, learned first 2/3 of the dataset and predict the subsequent 1/3] | 213.86 | 0.9634 | 148.65 | 172.16 |
| **Gaussian Processes** [Matern kernel with length_scale=1, nu=0.5] | 140.34 | 0.9867 | 99.02 | 107.42 |
| **Combination of physics-based model and Gaussian Processes** | 109.42 | 0.9919 | 74.75 | 71.39 |

## Acknowledgments

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