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A Physics Model Embedded Hybrid Deep Neural Network for Drillstring Washout Detection

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Abstract

One of the practical challenges in the oil and gas industry is the lack of quality data for applying machine learning techniques. A way to tackle this problem is to build a hybrid system that combines physics models with machine learning workflows. To demonstrate the applicability, the proposed hybrid model has been applied to drillstring washout detection which is relatively a common but severe and very expensive failure in drilling.

We propose a hybrid deep neural network (hybrid-DNN) composed of three components – Parameter Network (PNet) for estimating model parameters, Residue Network (RNet) for predicting regression or classification results, and a physics model appropriate for the problem at hand. PNet learns the system behavior based on the embedded physics model, which it controls through adjusting model parameters. RNet utilizes the outputs from the PNet and physics model as input and is being trained for predicting the residual. Once trained, the hybrid system can control the parameters of the physics model and predict the desired results in real-time.

The proposed hybrid system has been applied to drillstring washout detection. Traditionally, drillstring washouts have been detected by monitoring the trends of hydraulic coefficients between standpipe pressure and flow rate of the circulated drilling fluid. Several data-driven methods based on statistical change detection have been tried to automatically detect the occurrence of abnormal trends. However, most current applications struggle to identify true washout events since they largely overlap with normal drilling patterns in noisy measurements.

The hybrid-DNN has been verified by augmented drillstring washout cases and actual field events. When fed with a real-time data stream, it is able to extract the optimized model parameters and identify normal drilling conditions and potential washout situations. It also demonstrates that the hybrid-DNN predicts more reliable results without false-positives compared to the data-driven approach without a physics model. The proposed physics model embedded hybrid-DNN provides a general-purpose framework for many different domain problems based on physics.

Introduction

The combination of industry transforming machine-learning techniques and large volumes of digital data offer the potential to solve many different oil and gas industry challenges. However, there is a practical problem where the lack of quality data in sufficient quantities precludes these approaches. One way to tackle these data-poor problems is to build a hybrid system that combines models of physics with the machine learning workflows. The hybrid system should be able to take advantage of the many advances that machine-learning and data analytics have brought in recent years, while still leveraging the domain knowledge and effort incorporated in the physics models.

As a practical demonstration of the methodology, the proposed hybrid model has been applied to drillstring washout detection which is relatively a common but severe and very expensive failure in drilling. Traditionally, drillstring washouts have been identified by monitoring the trend of hydraulic coefficients between standpipe pressure and flow rate of the circulated drilling fluid as shown in Fig. 1. In the field, drilling engineers monitor the various real-time channels and detect drillstring washouts from standpipe pressure (SPP) anomalies in the context of other measurements. For example, in Fig. 1, the measured SPP data abruptly ramps down where there is no corresponding decrease in the flowrate. The intuitively drawn trend line of theoretical SPP has been used as a guideline to detect a washout event.

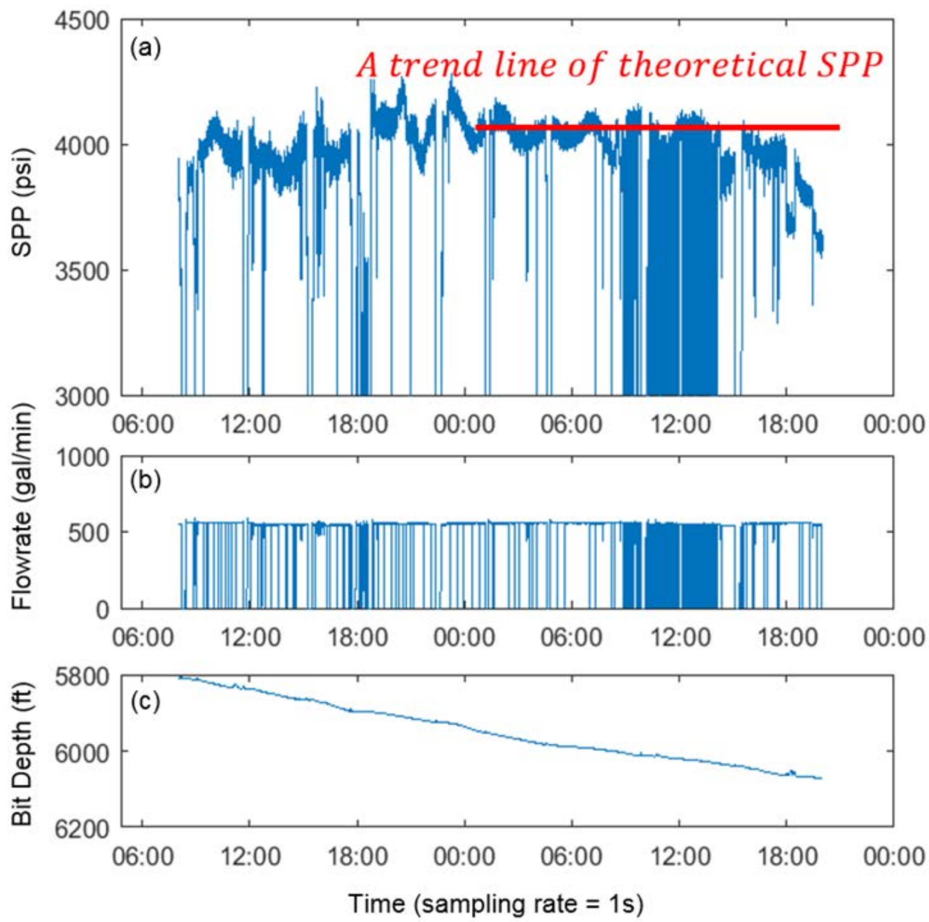

Figure 1—A typical pattern of drillstring washout observed in (a) Standpipe pressure, (b) Flowrate, and (c) Bit depth data.

To model the theoretical SPP systematically, various physics models have been proposed. The Darcy-Weisbach equation is one of the basic physics models to capture the relationship between standpipe pressure (P) and mudflow velocity (Q) in equation 1 (Nevers, 1970),

$$P = h \cdot Q^2 \tag{1}$$

where *h* is the hydraulic coefficient. This function assumes the hydraulic coefficient contains all the relationships of drillpipe and wellbore geometry, bit nozzle size, mud density, Fanning friction, and flow regime of turbulent or laminar. As shown in Fig. 2, a physics model is useful to predict a theoretical pressure systematically. Through the physical model and the modeled standpipe pressure, we can easily monitor the pressure anomalies quantitatively. However, it is nearly impossible to capture various drilling conditions, environmental changes in the well, and other complex interactions in a single coefficient. To predict the standpipe pressure behavior more accurately, various physics models with more inputs and parameters have been proposed and tested. Some of them show better accuracy for the washout detection in certain fields. However, there is no perfect model that can explain the standpipe pressure behaviors completely from the other measurements. Certainly, physics models are useful to predict the general trends based on the physical phenomena, even though the model cannot always tell where the pressure anomaly happens, and the results are often very noisy.

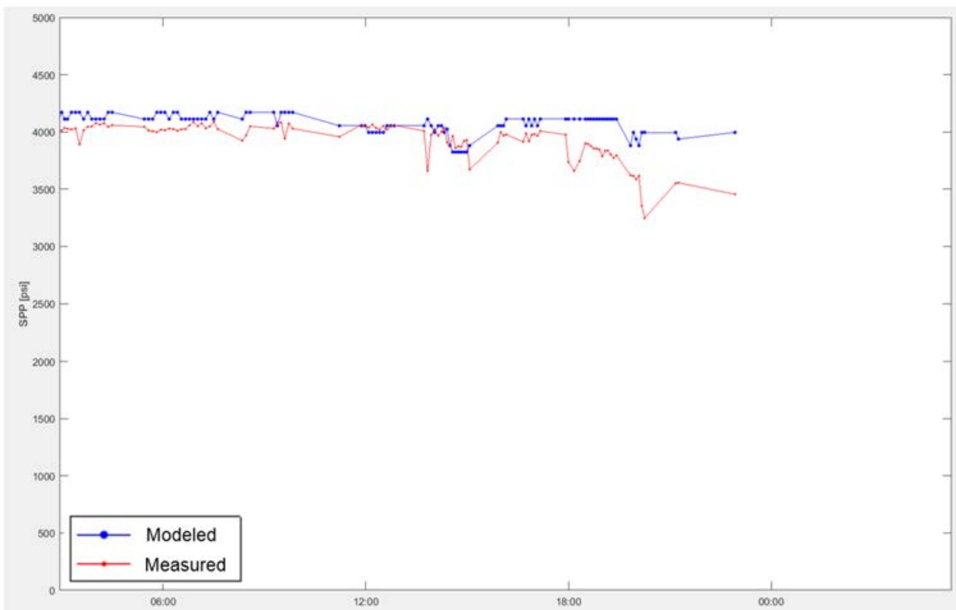

Figure 2—Drilling string washout behavior demonstrated by the modeled SPP (blue line) and the measured SPP (red line).

Several data-driven methods based on statistical change detection have been tried to automatically monitor the occurrence of abnormal trends (Aldred et al., 2008; Aldred et al., 2012; Wong et al., 2013; Anders et al. 2015). However, most of the current applications are struggling to detect true washout events that are largely overlapped with normal signal patterns in noisy measurements. Most of these algorithms have the ability to detect real drillstring washout events; however, the major problem is they detect too many false-positive events, as shown in Fig. 3. The first statistical model plotted in Fig.3 (a) as black dots follows the quick event detection algorithm (Aldered et al., 2008) and the second statistical model (marked as red dots in Fig. 3) is based on the improved change point anomaly detection algorithm which tries to reduce false alarms with more preset constraints. The testing results of the both algorithms for a normal drilling section of 6 days generated about 22% and 18% false alarms, respectively (see Fig. 3). Since the statistical change detection algorithms are designed to be sensitive for the change of trends in data points, it frequently creates false alerts when the input data is noisy.

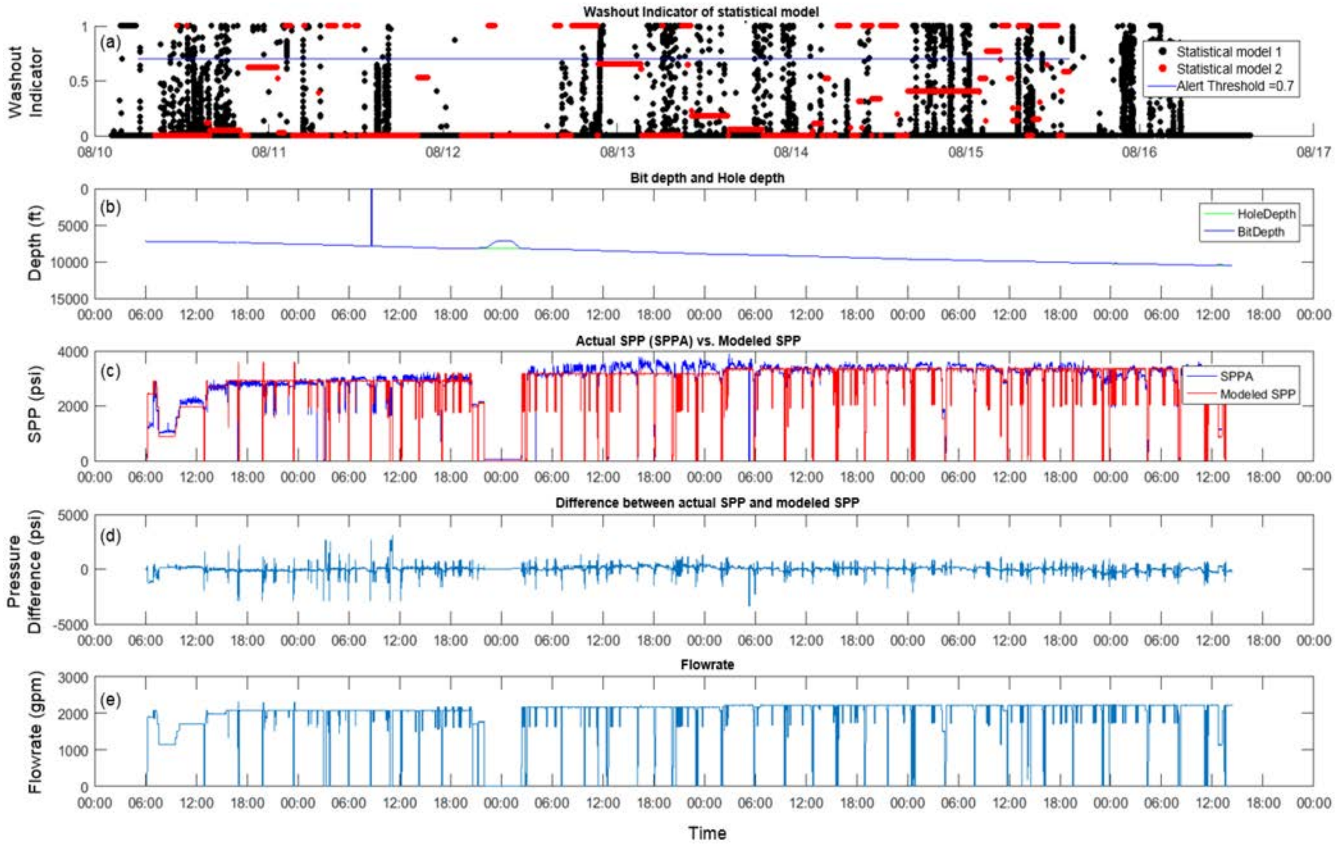

Figure 3—Results of washout indicators based on statistical change detection algorithms.

The proposed workflow tries to capture all patterns between the input data and the final washout label. A hybrid deep neural network is iteratively trained to find out the best parameters of the physics model which can explain the measured data, and to judge whether the difference between the model output and the data indicates a real washout.

Method

A hybrid deep neural network combining a physics model

The solution presented here, a hybrid deep neural network (hybrid-DNN), embeds physics models into a machine learning framework that can be trained by the available data (See Fig 4.). The hybrid-DNN is composed of three components – Parameter Network (PNet) for estimating model parameters, Residue Network (RNet) for predicting regression or classification results, and the physics model(s) appropriate for the problem at hand. PNet learns the system behavior based on the embedded physics model, which it controls through adjusting model parameters. In the drillstring washout detection problem, PNet is iteratively trained to find out the best parameters which make the modeled SPP match with the actual SPP. RNet utilizes the outputs from the physics model and PNet and trains a deep neural network to characterize the patterns and latent information in the derived parameters and data. Once trained, the combined system can predict the desired results and indicators based on a real-time data input stream. The proposed hybrid-DNN is an integrated system of physics model, its parameter setting, and the pattern detection in the residuals between modeled results and data.

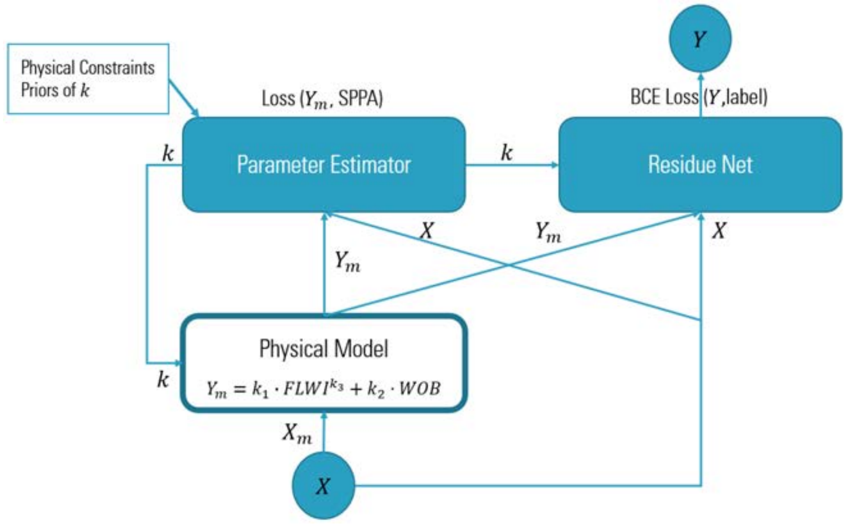

Figure 4—A system architecture of the proposed workflow for drillstring washout detection.

Deep Kalman Filter (DKF) as a deep neural network algorithm

Here, we applied the Deep Kalman Filter (DKF) as a deep neural network model (Yu et al., 2019). In general, the rig dynamic system can be modeled using Kalman filter in equation 2,

$$\begin{cases} X_t \leftarrow f(X_{t-1}) + b(U_{t-w:t}) \\ Z_t \leftarrow h(X_t) \end{cases} \tag{2}$$

where U is input of multi-channel time series within a window size *w* at time *t*. X is an internal state of the represented dynamic system, while Z is the observable, or the target class labels. f, b, and h are transfer functions. Yu et al. (2019) demonstrated the DKF algorithm as a deep neural network is applicable to generate simulated time series data with control signals and characterize the different drilling sequences. Thus, the proposed hybrid-DNN used the DKF algorithm for integrating the PNet outputs and the physics model in the RNet.

Fig. 5 illustrates the architecture of DKF applied to the drilling string washout detection problem. The DKF contains the transfer functions in equation 2 with convolutional layers, recurrent layers (GRU), and fully connected layers correspondingly. The first 10 layers including the input layer, 6 convolutional layers, and 3 max pool layers learn the b transfer function converting the input time series data to internal hidden state. For the f function, the 3 recurrent layers learn the internal state update. The final 5 layers in the h function translate the internal state to the final judgment of washout or non-washout.

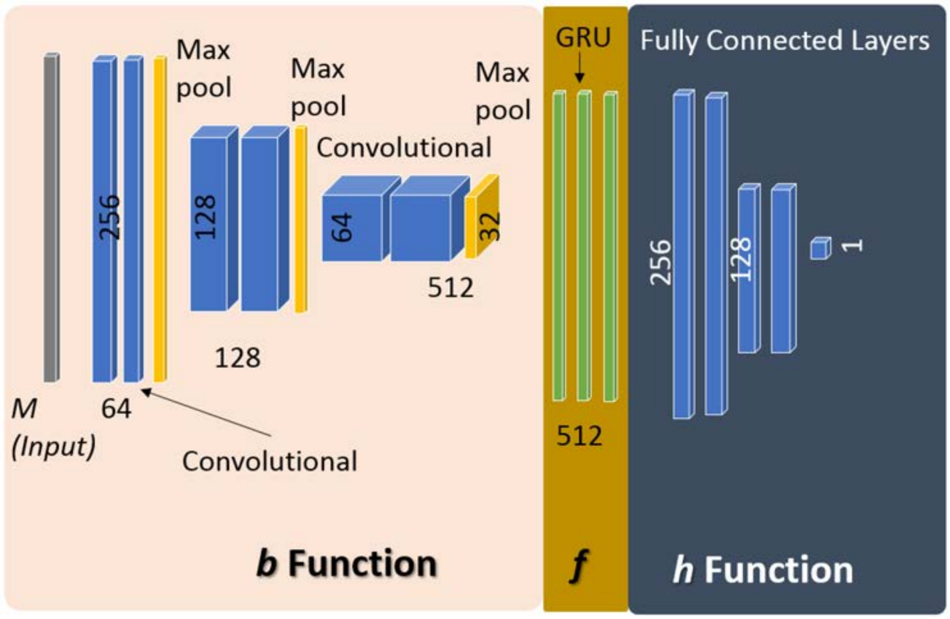

Figure 5—Architecture of the applied DKF layer structure.

Application

Data augmentation for model training

The goal of the model training is to capture suitable parameters for the physics model and the actual data. The parameter estimation process has to be integrated with the final washout detection comprehensively by algorithm design. To train the patterns of washout involved with various drilling measurements and parameters of physics model, we used augmented drillstring washout cases shown in Fig. 6. The augmented cases based on actual field datasets including actual drillstring washout cases. As a practical challenge, the total number of drillstring washout cases is relatively small compared to the non-washout cases. Therefore, we augmented the washout behaviors as standpipe pressure drop. The augmentation is randomized for fast washout and slow washout cases and it is designed to happen at any position in the actual timeline.

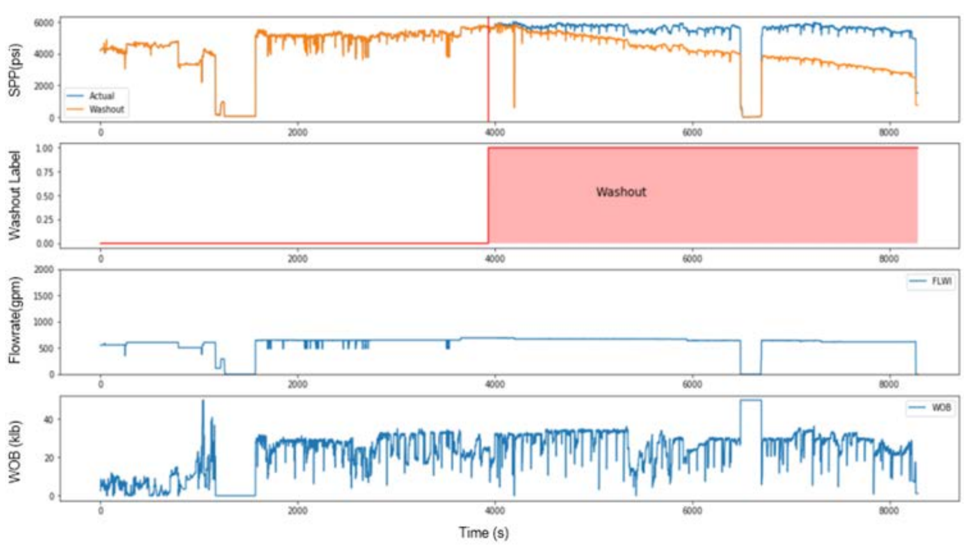

Figure 6—Augmented drillstring washout cases based on the actual field data.

Model testing

Next, the trained hybrid-DNN model is used to predict a drillstring washout event for the unseen field cases. Fig. 7 illustrates the actual standpipe pressure data and the washout prediction result predicted by the proposed model. The prediction result shows the trained model is quite accurate compared to the reference of the actual washout label. We can observe a very short false positive prediction near the 4000 seconds in time (x-axis). For sure, there would be more room to improve the algorithm with more training with more informative large quantity of datasets. However, the current results show promising predictability since the sensitivity to the washout events is somewhat a tradeoff with false positives. The goal of the machine learning model we proposed is not a perfect method to detect better than human experts but a reliable solution which can exclude the unrealistic noisy events as a human would do. Fig. 8 shows an example of detection with noisy data. The trained model switches between true and false for the washout until it collects sufficient data points to be sure, near 4700 seconds in time (x-axis). Even for a domain expert, it is a really difficult challenge to decide the actual washout correctly in real-time since the noisy field data fluctuates a lot.

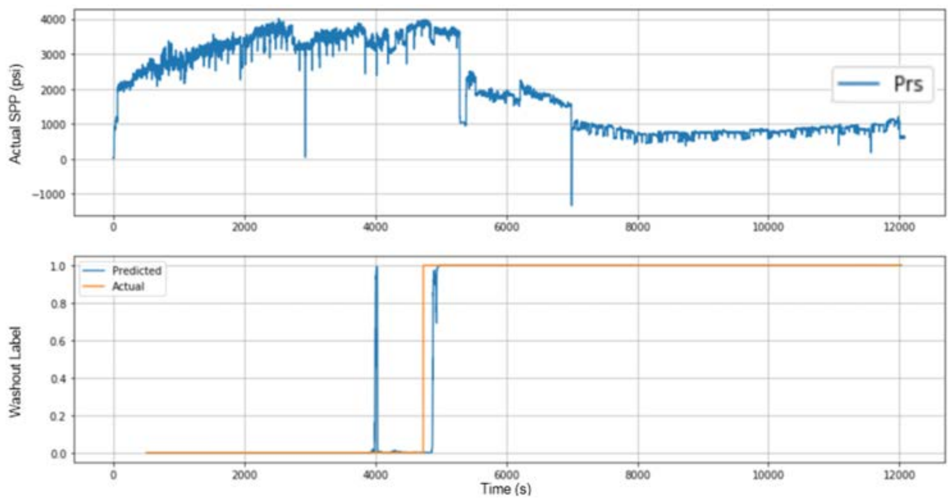

Figure 7—Drillstring washout prediction results for the unseen washout case.

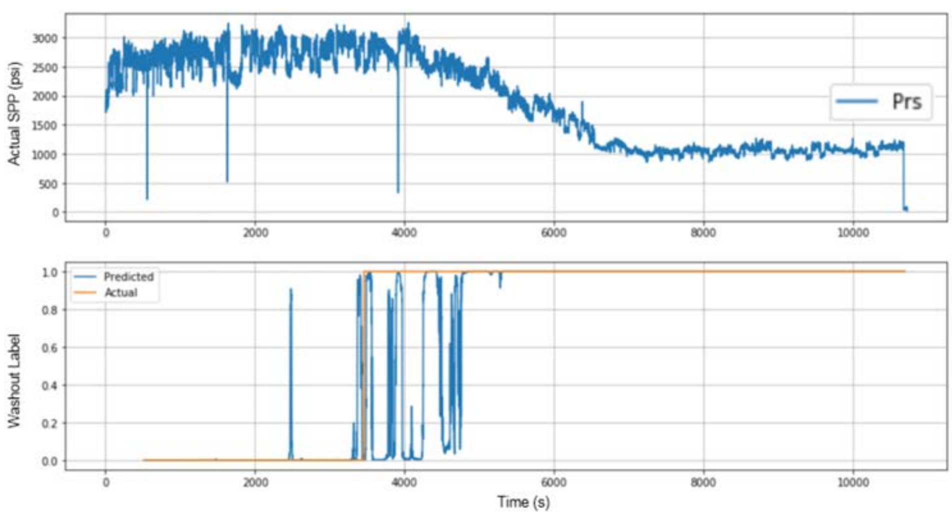

Figure 8—Drillstring washout prediction results for the noisy field case.

Model validation

The hybrid-DNN has been tested with artificial drillstring washout cases and actual field cases. When fed with a real-time data stream, it is able to extract the optimized model parameters and identify normal conditions and potential washout situations. It also demonstrates the hybrid-DNN predicts more reliable results without false-positives compared to the data-driven approach without a physics model (See Fig. 9). The same DKF model fully trained by datasets only shows very noisy alarm patterns as we observed in Fig. 3. The data-driven model sensitively detects the pressure drops and classifies it as potential washout events frequently since the trained model has only learned the patterns of data combination. In contrast, the physics model embedded hybrid-DNN minimizes false-positive labels while preserving the same level of event predictability (detect a washout event as washout). Fig. 10 summarizes the iterative test results with 100 different case studies. With the full validations of 100 trials, we can conclude that the hybrid-DNN with physics model is a more accurate and reliable solution than the data-driven deep neural network model.

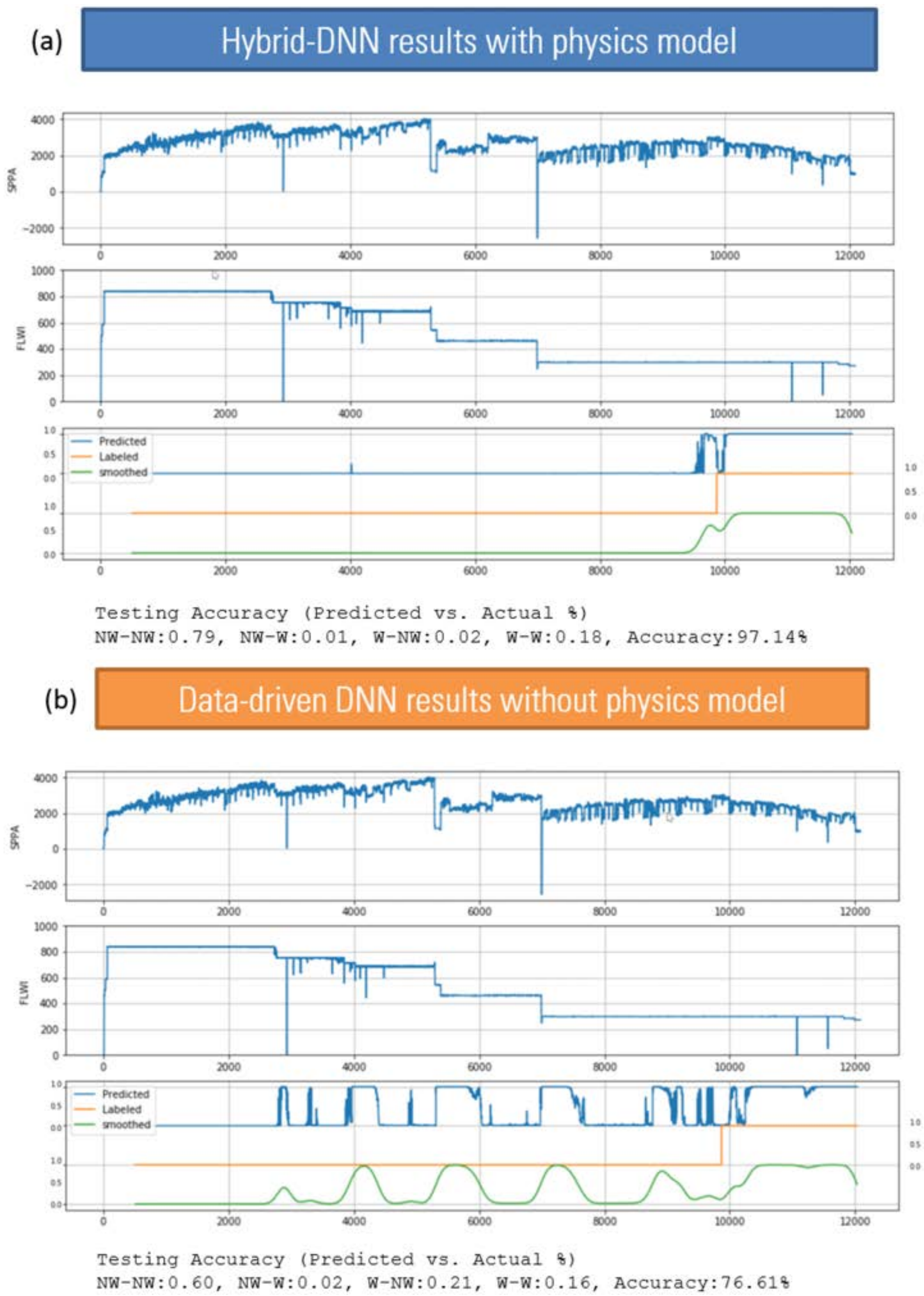

Figure 9—A comparison between (a) the hybrid-DNN with physics model and (b) the fully data-driven DNN method without physics model.

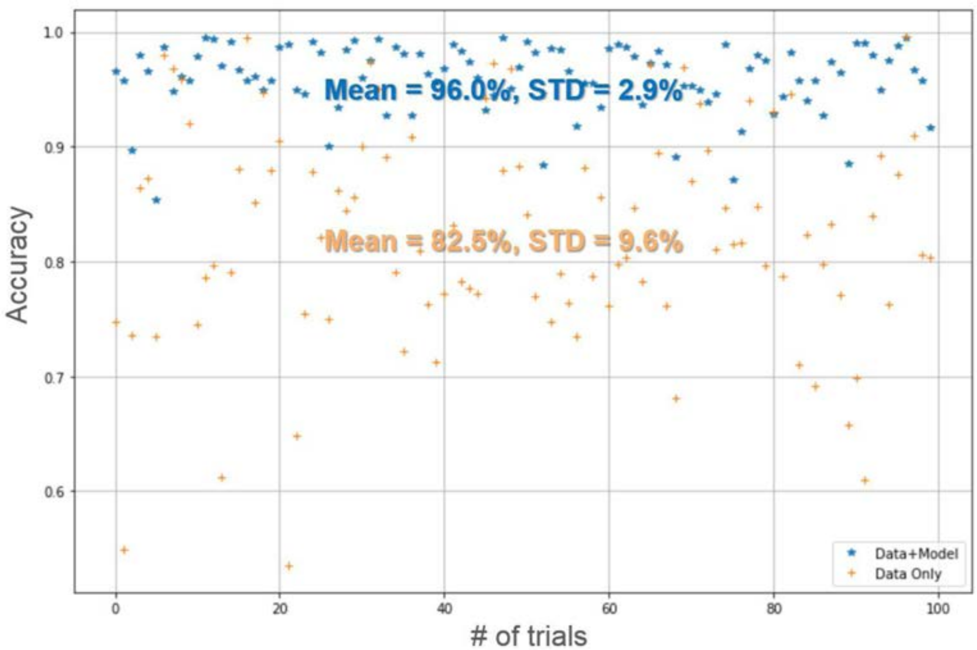

Figure 10—A physics model (data+model) helps to reach more reliable predictions than data-driven approach (data only) for washout detection

Conclusion

The proposed hybrid-DNN provides a general-purpose framework for combining physics models with machine learning techniques, helping develop more reliable solutions. It takes advantage of advanced data analytics and machine learning while leveraging the decades of knowledge and effort incorporated in the physics models. As a practical demonstration, it is applied in drillstring washout detection, incorporating a simple model of the physics. From the application results, we can conclude that the hybrid-DNN with the physics model can be a more accurate and reliable solution than the data-driven deep neural network model since it maximizes the interpretability resolved in the physics model and the power of DNN capturing the latent patterns of data and parameters.

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