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Downhole Pressure Estimation Using Committee Machines and Neural Networks

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Abstract: In gas-lifted oil wells the monitoring of downhole pressure plays an important role. However, the permanent downhole gauge (PDG) sensor often fails. Because maintenance or replacement of PDGs is usually unfeasible, soft-sensors are promising alternatives to monitor the downhole pressure in the case of sensor failure. In this paper, a data-driven soft-sensor is implemented to estimate the downhole pressure using committee machines composed by finite impulse response (FIR) neural networks. Experimental results in three real datasets of the same oil well indicate that the identified soft-sensor is able to predict the downhole pressure with satisfactory accuracy. The model input variables were selected by statistical tests which increased insight concerning such variables. Committee machines outperformed single-model soft-sensors on experimental data.

Keywords: downhole pressure, neural networks, ensemble, soft-sensor, sensor failure.

1. INTRODUCTION

The soft-sensors are mathematical models capable of estimating a process variable using measurements of other process variables. They have been used in many industrial applications as process monitoring and sensor fault detection (Fortuna et al., 2007). According to (Kadlec et al., 2009) there are three classes of soft-sensors: model-driven, data-driven and hybrid. The model-driven soft-sensors are based on first-principle models, called white-box models, whilst data-driven soft-sensors are based on models identified using data available from the process, or black-box models. Finally, there are those that incorporate features of these two previous classes, called hybrid soft-sensors.

In the oil industry, one important application of soft-sensors is to estimate the downhole pressure of oil wells, since the monitoring of this pressure allows engineers to optimize production techniques (Eck et al., 1999; Wang and Li, 2013). However, the permanent downhole gauge (PDG) sensor failure often happens (Teixeira et al., 2014). Due to the difficulty in accessing the sensor installation site, soft-sensors are promising alternatives to monitor the downhole pressure when the sensor measurements are no longer available.

Due to their universal approximation capability, Neural Networks models have been widely used to develop soft-sensors (Gonzaga et al., 2009; Roverso, 2009). To improve model performance, *committee machines* can be built (Soares et al., 2011; Sui et al., 2011). The field of committee machines studies the combination of models. As a rule of thumb, combining estimators is more robust and accurate than using a single one (Perrone and Cooper, 1993).

Committee machines can be divided into two groups: *ensemble* and *modular* architectures. The former combines redundant predictors in the sense that each one could solve the task as a whole (Hansen and Salamon, 1990), however, the best result is expected to be achieved by using the combination. In the modular approach, the problem is divided into different sub-tasks and each predictor takes charge of a sub-task whereas the final solution has to be composed of all predictors (Sharkey, 1999).

Thus, the objective of this work is to implement a data-driven soft-sensor to estimate the downhole pressure of a real oil well. The contribution of this paper is to introduce a procedure to select input variables of neural models using statistical tests, and to design *ensembles* composed by Neural Networks models to estimate the downhole pressure. Besides a discussion about some relationships among oil process variables is also presented.

This paper is organized as follows. In Sec. II, a simplified description of the investigated process is presented. The Materials and Methods are presented in Sec. III and Sec. IV presents the results. Conclusions are drawn in Sec. V.

2. PROCESS DESCRIPTION

The offshore oil extraction process involves extracting the oil contained in reservoirs located below the seabed using floating platforms or vessels. These are responsible for

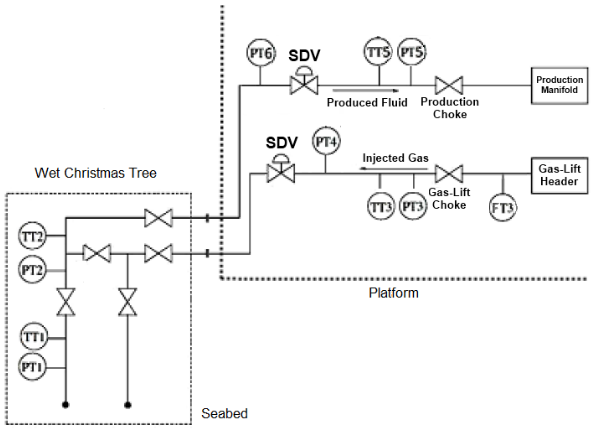

Fig. 1. Simplified P&ID diagram of a gas-lifted oil well. The corresponding variables are described in Tab.1.

Table 1. Process variables. Tags correspond to the codes shown in Fig. 1.

Tag	Process Variable	Location
PT1	Downhole pressure	Seabed
TT1	Downhole temperature	Seabed
PT2	Wet Christmas Tree pressure	Seabed
TT2	Wet Christmas Tree temperature	Seabed
PT3	Pressure downstream of gas-lift choke valve	Platform
TT3	Temperature before gas-lift shutdown valve	Platform
FT3	Instantaneous gas-lift flow rate	Platform
PT4	Pressure upstream of gas-lift shutdown valve	Platform
PT5	Pressure upstream of production choke valve	Platform
TT5	Temperature before production choke valve	Platform
PT6	Pressure upstream of shutdown valve	Platform

the production management, storage and, in some cases, primary processing of the production.

When there are several wells being managed by the same platform, *manifolds are used*. Such pieces of equipment are responsible for the simultaneous production of different wells and may be located at the seabed, and connected to the respective *wet Christmas tree* (WCT). In offshore oil extraction, the *continuous gas-lift method* is usual choice for artificial lift in mature wells (Jadid et al., 2006).

This technique consists of injecting pressurized gas in the production string continuously in a controlled manner. Choke valves located at the platform are used to control the amount of gas. Precise control of the gas-lift operation is necessary, since the ratio of produced oil and injected gas is non-linear, meaning that increasing the gas injection after a point does not correspond to higher production (Ray and Sarker, 2007; Jadid et al., 2006; Singh et al., 2013).

In order to monitor and control the gas-lift system and the oil production, data from several sensors are available to the operator (Fig. 1). One of the available sensors is the PDG sensor (PT1 and TT1), located inside the production string. This location enables the measurement of valuable data for the efficient operation of the production but also renders the sensor subject to intense wear.

Despite improvements in the construction, PDG sensors still have a short lifespan. Approximately 30% of the sensors fail within 5 years of installation (Frota and Destro, 2006). There is, also, a great difficulty or even an impossibility of replacement or maintenance of the sensors due to their location. To perform this tasks, it is usually necessary to stop production, causing major economical losses.

Table 2. Experimental datasets.

Datasets	Size (samples)	Use
A1	55,615	training and validation
A2	95,586	test
A3	41,760	test

Therefore, on the one hand, PDG sensor is a valuable tool to achieve efficient production and, on the other, sensor lifespan is relatively short with replacement or repair being sometimes economically unfeasible. In this context, soft-sensors become alternatives to increase data reliability or even act as a substitute in cases of sensor failure. Thus, this work aims at implementing soft sensors for the downhole pressure (PT1).

3. MATERIAL AND METHODS

3.1 Experimental Data

We will use data from various sensors to identify models to estimate the downhole pressure. In this investigation, the input variables are restricted only to those measured from platform sensors. In a less conservative study variables from the WCT could also be considered.

Three datasets from the oil well A are available. The sampling frequency of these datasets is 1 sample/minute and Tab. 2 summarizes their size and application during the model estimation process. Figure 2 shows the downhole pressure to be estimated for each dataset. Dataset A1 was used to train the neural models and to define their structures (train and validation). Generalization performance was evaluated on the dataset A2 (test). Dataset A3 shows the moment the PDG fails (test).

3.2 Neural Network Models and Committee Machines

In this work, only FIR (Finite Impulse Response) black-box Neural Network (NN) models are identified which can be represented by

$$\begin{aligned} y(k) = F[&u_1(k-1), ..., u_1(k-n_{u1}), \\ &u_2(k-1), ..., u_2(k-n_{u2}), \\ &u_n(k-1), ..., u_n(k-n_{un})], \end{aligned} \quad (1)$$

where F is a non-linear function implemented by feed-forward multi-layer perceptron neural networks (MLPs), and n_{u_i} is the maximum delay of the input u_i, where $i = 1, \ldots n$ and n is the number of inputs. We choose the FIR structure to prevent obtaining unstable models since the objective is to perform model free run simulation. The model inputs are the following variables measured from oil platform sensors: pressure upstream of the shutdown valve, pressure upstream of the production choke valve, temperature before production choke valve, pressure upstream of the gas-lift shutdown valve, temperature before gas-lift shutdown valve and instantaneous gas-lift flow rate.

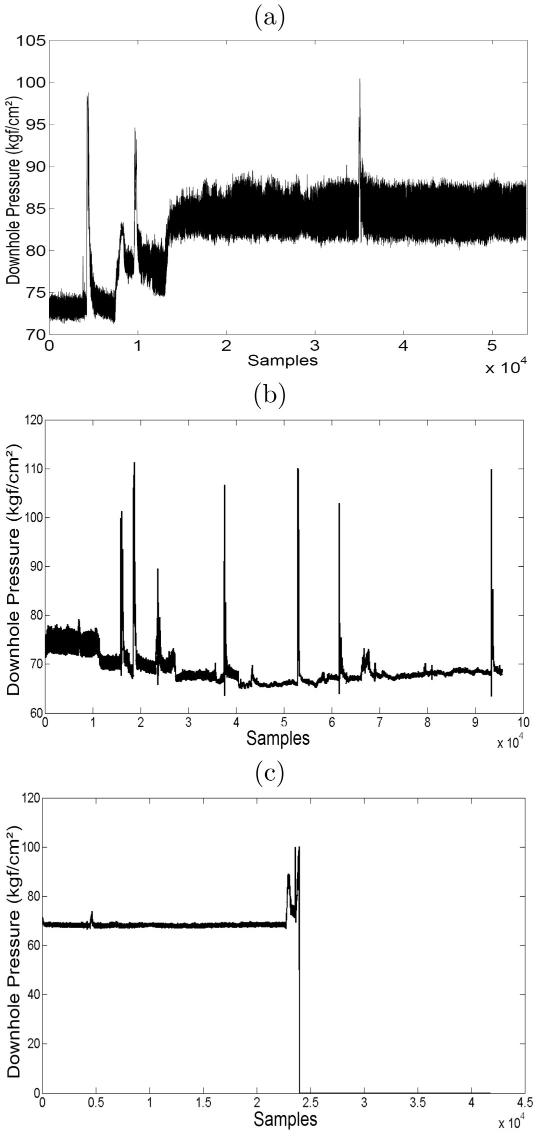

Fig. 2. Downhole pressure of available datasets: (a) A1, (b) A2 and (c) A3 (see Table 2).

From this model structure, the goal becomes the estimation of the neural network parameters (training process) that is accomplished using the LevenbergMarquardt algorithm. To improve models performance, committee machine are employed.

An ensemble with components that are less correlated, (i.e. there is diversity within the committee), are likely to have better generalization (Barbosa et al., 2011). In this way, one important feature to be explored in the construction of ensembles is diversity (Liu and Yao, 1999; Brown et al., 2005). However, the search for diverse members may result in individuals with poor generalization. So, there is an optimum balance to be achieved (Brown et al., 2005).

Based on how diversity is created, Brown et al. (2005) presented a categorization of ensemble methods: (i) starting point in hypothesis space: for example varying the initial weights of a network; (ii) set of accessible hypothesis: changing the input training data of each member as the techniques *bagging* (*bootstrap aggregating*) (Breiman, 1996) and *boosting* (Schapire, 1990) or manipulating the architecture of the components; (iii) hypothesis space traversal: which includes penalty methods (Liu and Yao, 1999) and evolutionary approaches (Barbosa et al., 2011).

Algorithm 1 *Bagging*

Choose the learning algorithm L, the number M of estimators f_i and the number of samples N_{bag}
for $i = 1, \ldots, M$ **do**
  Compose a new training set, T_{bag}, with N_{bag} samples, randomly chosen (with replacement) from the original training set T
  Train the ith estimator: $f_i = L(T_{\text{bag}})$
end for

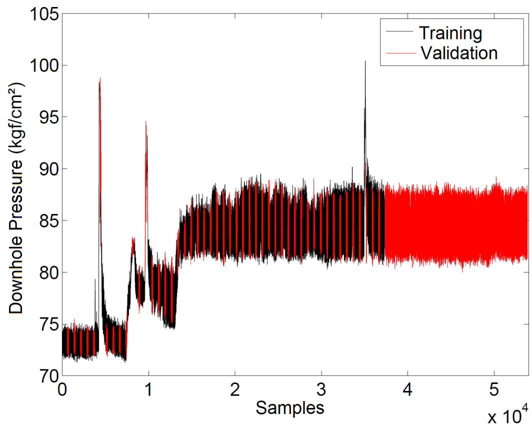

Fig. 3. Training (black) and validation (red) sets of A1. Some details of this dataset are shown in Fig. 7 where the downhole pressure dynamic behaviour can be better observed.

Bagging (Algorithm 1) is one of the most popular techniques for creating committees, it is based on the resampling of training patterns to obtain different training subsets for each *ensemble* member (Breiman, 1996). In this technique, subsets are randomly generated by sampling with replacement the original data set, some observations may be repeated among the generated subsets.

To design the ensembles, decisions need to be made with respect to the choice of the committee size (number of ensemble members), the combination procedure, and the models architecture and parameters (Barbosa et al., 2011). Each ensemble member is a neural network composed by hidden nodes with hyperbolic tangent activation function and one linear output node. The *ensemble* output, f_{ens}, is the average of the M components outputs, f_i.

The original dataset is divided into several training (600 samples) and validation (150 samples) windows. The final samples are separated for validation as shown in Fig. 3. Each Neural Network is trained using 25% of the available training samples chosen by the *bagging* algorithm.

4. EXPERIMENTAL RESULTS

Figure 1 shows that seven process variables are available from platform sensors to construct the downhole pressure soft sensor. There are many other variables available, such as valve positions, but the ones considered the most informative for this well were chosen. For instance, the pressure downstream of the gas-lift choke valve (PT3) was exclude since it was corrupted by noise. Thus, six platform variables may be used for model identification.

Using dataset A1 (Fig. 3), two data groups were defined:

- Group 1: data from 5,000 to 15,000 samples;
- Group 2: data from 20,000 to 30,000 samples.

These groups were selected to study the influence of variables for predicting distinct dynamics of the downhole pressure: changing of operating point (Group 1) and severe slugging (Group 2). After some Fourier analysis and trial and error experiments, the lags of the neural model inputs, n_{u_i} (see Eq. 1), were defined as [1, 42 and 136] for variables related to the gas-lift injection and [1, 5 and 22] for variables related to the produced fluid measurements. The number of hidden nodes (ten) of the Neural Network was also chosen comparing performances of NN with 5, 10, 15 and 20 hidden nodes.

To define which of the six platform variables would be used, several tests were implemented that consisted in training 100 Neural Networks (training data: 70% of the data samples of Groups 1 and 2) such that one of the six variables was excluded as model input and the tests performance were compared to the results obtained by neural models identified using the six variables on validation data (the remainder 30% of data samples of each group). A multiple comparison procedure was implemented using the Tukey's honestly significant difference criterion, based on the Studentized range distribution (confidence level of 95%) on validation data of Group 1 and on validation data of Group 2. If the mean squared error (MSE) of a variable exclusion test is significantly greater than the MSE of the test where no variable was excluded, it indicates that the excluded variable is important to predict the downhole pressure.

It is pointed out from the results (see Fig. 4): (a) that when the instantaneous gas-lift flow rate (FT3) or temperature before production choke valve (TT5) were excluded the model performance deteriorated (Fig. 4a) in relation to a model in which no variable was excluded, so they should be kept as model inputs; (b) the pressure upstream of the production choke valve (PT5) and pressure upstream of the shutdown valve (PT6) should be also kept as inputs (Fig. 4b).

Therefore, only the variables like temperature before gas-lift shutdown valve (TT3) and pressure upstream of the gas-lift shutdown valve (PT4) can be excluded from the model without loss of performance. However, the use of PT4 renders training more robust, thereby it will be kept. The final neural model structure identified is shown in Fig. 5.

Figure 4 also reveals an interesting relationship. Variables related to gas-injection are important to predict the downhole pressure operating points whereas variables related to the fluid production are important to predict severe slugging. This is more evident when the variable temperature before production choke valve (TT5) is analysed.

As discussed before, committee machines usually achieve better generalization performance than a single estimator. Thus, we compared the performance of a committee

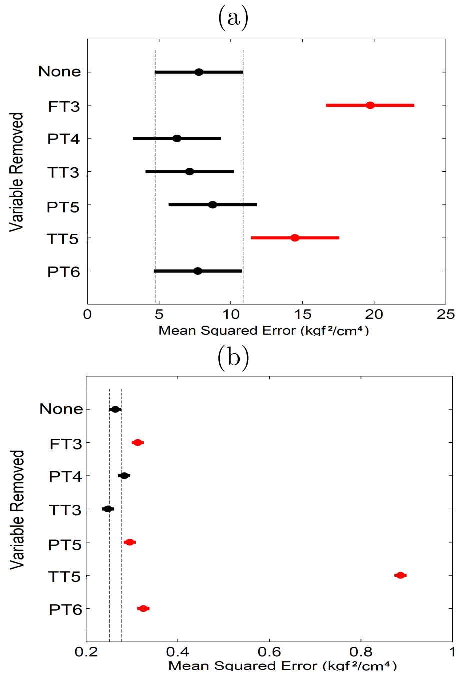

Fig. 4. Input variable analysis using Turkey's statistical test (95% confidence level - 100 Neural Networks were identified for each test), (a) Group 1 and (b) Group 2.

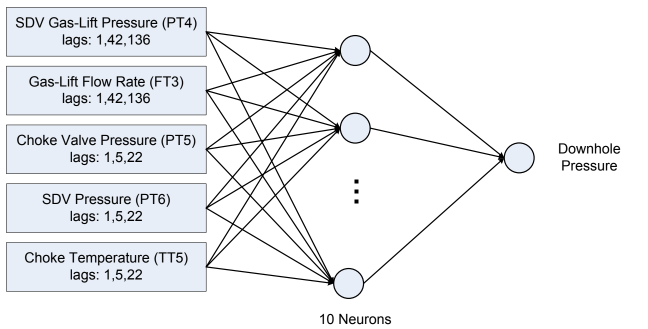

Fig. 5. Neural Network structure.

machine composed of 10 neural networks to a single neural network (Fig. 6). As expected, the committee outperformed the single estimator. The ensemble size was selected applying statistical tests. Due to space constraints, only the best result (10 members) is presented.

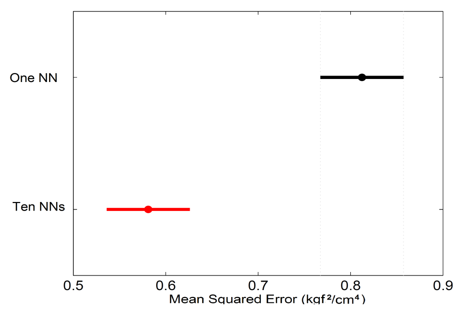

Fig. 6. Committee machines performance analysis using Turkey's statistical test (95% confidence level - 100 Neural Networks or Committee Machines were identified for each test).

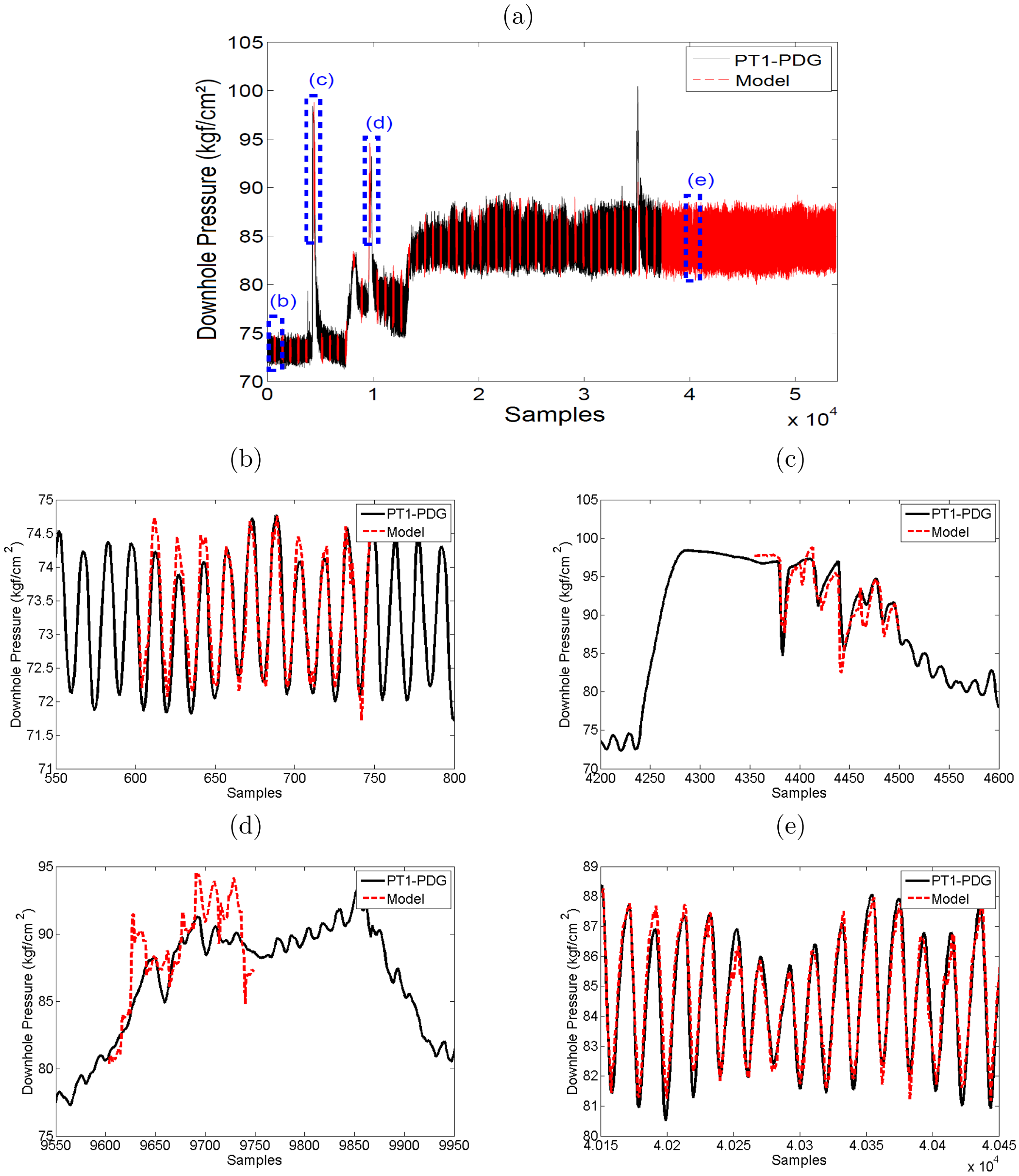

Fig. 7. Committee machine simulation on validation dataset A1: (a) total window, (b)–(e) detailed views. Only model simulation on validation data windows is shown.

The simulations of the estimated committee over the validation datasets A1 and A2 are presented in Fig. 7 and Fig 8 (a), respectively. It can be inferred that the model is able to predict the downhole pressure with good accuracy. In such cases, the mean absolute percentual errors (MAPE) were 0.45% for dataset A1 (validation) and 1.49% for dataset A2 (generalization test error). These results are very competitive if compared to the results presented in (Teixeira et al., 2012, 2014).

Aiming at evaluating the model performance over dataset A3 (sensor failure), we used data from PT2 (Wet Christmas Tree pressure). It was previously observed that such a variable has a very similar behaviour to the downhole pressure in this oil well and it was not used as model input variable. So, Fig. 8 (b) presents the model prediction of downhole pressure on dataset A3 and measured PT2. It can be seen than their behaviour are very similar indicating that the model is probably predicting well the downhole pressure when it is no longer available.

5. CONCLUSIONS

In this paper a data-driven soft sensor is designed for prediction of downhole pressure in gas-lifted oil wells. Combinations of Neural Networks, called Committee Machines, are employed to estimate the downhole pressure. The selection of input variables was realized using statistical tests. These tests were shown to be appropriate to select the input variables and also to study the influence of some variables in distinct system dynamics.

As expected, the use of combination of estimators improved the soft-sensor performance. A simple ensemble creation procedure was implemented (bagging) and the ensemble yielded a MAPE less than 1.5% in two experimental datasets.

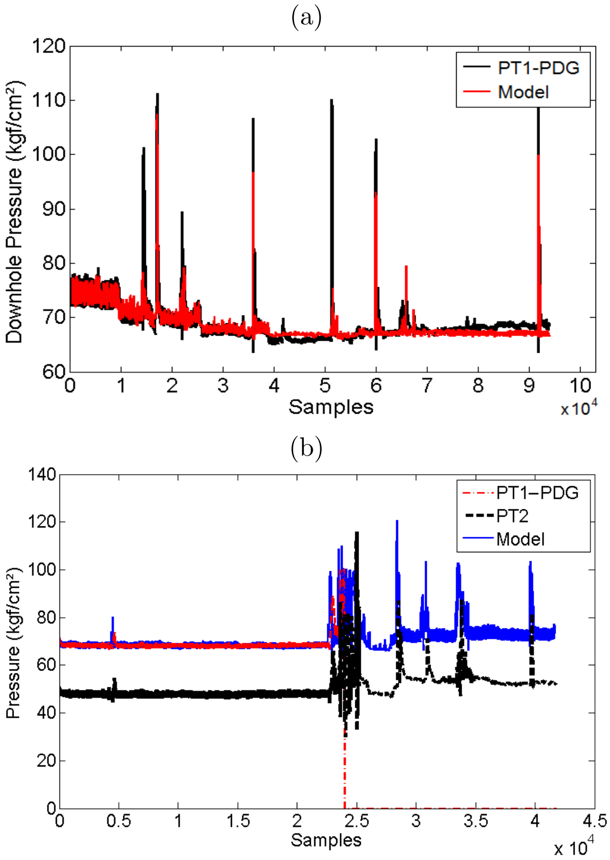

Fig. 8. Committee machine simulation over the datasets: (a) A2 and (b) A3.

Future studies will examine different ensemble techniques like boosting and will analyse if the mixture of experts approach is more appropriate, defining models for each operating point. Besides, it is also desired to implement an automatic algorithm to define the lags of the input variables, which is a computational NP-hard problem. To solve this automatically specific optimization algorithms should be built.

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